Expected Profitability

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Abstract

Current profitability is the de facto proxy for expected profitability in empirical investigations of present value models. I show that past growth in profitability significantly improves forecasts of future profitability over and above current profitability. Past growth in profitability is also related to future returns, even after controlling for current profitability, book-to-market ratios, investment, and past returns. Expected profitability, derived through a combination of current profitability and past profitability growth, generates larger return premia than current profitability.

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1 Introduction

Present value models are foundational to research in finance, accounting, and economics.[1] Applications of these models require estimates of expected future profitability. Researchers and practitioners either explicitly forecast future cash flow growth rates, assume that expected growth rates are reflected in current valuation ratios, or use current profitability as a proxy for future profitability. Leading empirical models use the last approach, consistent with the view expressed by Black (1980) that current earnings are the best measure of future earnings. For example, Fama and French (2006, 2015), Ohlson (1995), Vuolteenaho (2002), and many others use current profitability while invoking clean-surplus accounting to understand the dynamics of discount rates, book values, expected investment, and expected profitability. Applications of q-theory (Cochrane (1991), Liu, Whited, and Zhang (2009)) also use current profitability as an estimate of expected profitability (Hou, Xue, and Zhang (2015)). In this paper, I ask two questions. First, does past profitability growth improve estimates of future profitability. Second, if the answer to the first question is affirmative, is past profitability growth informative for future returns?[2]

To address the first question, I estimate annual cross-sectional regressions of future profitability ($t+\tau$) on past profitability growth controlling for other variables known to predict future profitability (current profitability, size, book-to-market ratios, and proxies for expected investment). As is well-known, average slopes on current profitability are reliably positive, indicating persistence and justifying the use of current profitability as a proxy for expected profitability. But surprisingly different from Fama and French (2006), I find robust evidence that past profitability growth *negatively* predicts future profitability. Importantly, past profitability growth increases the explanatory power of the regressions with a partial R^2 of 9%, a significant improvement in the description of the data generating process for future profitability. A partial adjustment model of future profitability growth that includes expected profitability as a regressor provides further evidence of mean reversion – depending on the specification, between 10% to 35% of past growth in profitability is subsequently reversed. There is a natural economic interpretation to these results: highly profitable firms attract competition from new entrants which reduces future profitability, and highly unprofitable firms have their assets redeployed via the market for corporate control or the bankruptcy code to more profitable endeavors.

[1] Variants of dividend discount models appear in each of these fields. Early studies include Campbell and Shiller (1988), Gordon (1959), Miller and Modigliani (1961), Ohlson (1995), Williams (1938).

[2] Some researchers regard expected profitability as a variable that should be naturally priced via present value models while others regard profitability as an asset pricing anomaly. In the open source asset pricing databases produced by Chen and Zimmermann (2022), Jensen, Kelly, and Pedersen (2023), and Kozak, Nagel, and Santosh (2020) profitability is labeled as an anomaly.

Given the above empirical regularity, I ask if past profitability growth contains incremental information for future returns. Fama and MacBeth (1973) regressions provide affirmative evidence. Average slopes on past profitability growth are negatively related to future returns, controlling for size, book-to-market ratios, investment, past returns, and most importantly, current profitability. In a baseline specification, for example, the average slope on past profitability growth is -0.10% (t-statistic = 2.81), even when the average slope on current profitability is 0.37% (t-statistic = 5.35). Interestingly, there is some evidence of non-linearity in the relationship. Consistent with the competitive dynamic described above, an interaction term between current profitability and past profitability growth is negative, and much of the degradation in future returns occurs in firms with high profitability and high past growth in profitability. These results suggest several different possibilities. Past profitability growth may be negatively related to future returns if investors irrationally bid up prices of stocks with high past profitability growth. This excessive extrapolation leads to lower future returns as realizations are lower than expected. It is also possible that, independent of current profitability, high past profitability growth is negatively related to priced risk. The channel for such a risk reduction, however, is not clear. The present value explanation is more straightforward – since past profitability growth contains negative information about future profitability, holding prices constant, discount rates must be lower.

As usual, it is difficult to distinguish between such non-mutually exclusive alternatives. La Porta (1996) uses analysts' expectations of growth to break a similar logjam in the context of value versus glamour stocks (see Lakonishok, Shleifer, and Vishny (1994) and Fama and French (1995) for the original disagreement). More recently, Delao, Han, and Myers (2024) use analysts forecasts of returns and cash flows to explain variation in valuation ratios. In the subjective beliefs literature, Bordalo, Gennaioli, La Porta, and Shleifer (2024) use analyst's expectations to shut down cross-sectional variation in expected returns so that all pricing errors are due to expectational errors. Bouchaud, Krueger, Landier, and Thesmar (2019) argue that analysts underestimate future profits when current profits are high because they have sticky expectations; this causes returns to be positively related to both the level and past growth in profitability, contrary to the negative average slope on past profitability growth in the return regressions described above. Following this line of inquiry, I extract expected growth rates from analyst forecasts and apply them to current profitability to generate estimates of one-period-ahead expected profitability. I then ask if expected profitability measured in this way is related to future returns. The average slopes on expected profitability using analysts' expectations are indistinguishable from zero. This is in contrast to Bouchaud, Krueger, Landier, and Thesmar (2019) who report that on average, analysts are too pessimistic about the future profits of high profitability firms. But it is

consistent with the evidence in Bordalo, Gennaioli, La Porta, and Shleifer (2024) who report that profitability is the sole exception in the ability of their errors-in-expectations approach to explaining the cross-section of returns. The non-result in my regressions implies that (a) expectations of future profitability are neither excessively extrapolative nor sticky, or that (b) analysts expectations are a poor measure of marginal investor expectations and discount rates.[3]

Failing to find evidence of biased expectations does not necessarily mean that expectations are not biased, but progress can be made on the present value front by measuring expected profitability using cross-sectional methods. I measure expected profitability using fitted values from the above-described annual cross-sectional regressions that predict future profitability using current profitability, past profitability growth, size, book-to-market ratios, and prior investment. This wholistic approach address the fact that expected profitability is a function of size and expected investment – important features of dividend discount, q-theory and other models. And since price is the denominator in book-to-market ratios, the fitted values also include the expected infinite stream of expected profits embedded in market prices.

In Fama and MacBeth (1973) return regressions, average slopes on current profitability and expected profitability can be interpreted as return premia associated with unit exposure (Fama (1976)). The average slope on current profitability (which serves as the benchmark case) in the 1975-2024 sample period is 0.34%, with a t-statistic of 5.04.[4] The average slope on expected profitability is more than double, 0.77% with a t-statistic of 3.98. While this is a large increase in return premia, I also quantify the increment by calculating the monthly return difference attributable to a change in profitability from the 25th to the 75th percentile. The time series average of that monthly return difference for expected profitability is 0.21%, compared to 0.11% for current profitability; in other words, the average cross-sectional spread in returns from expected profitability is almost double that from current profitability. A natural concern is that average slopes can be driven by large numbers of tiny stocks. In the all-but-microcap sample, however, the increases in average slopes are even larger, rising from

[3]Bordalo, Gennaioli, La Porta, and Shleifer (2024) provide evidence against the possibility that analysts extract expectations from current prices. On the other hand, Chaudhry (2025) shows that even if analysts' have biased beliefs, if they also learn from current prices, this introduces rational discount rate variation into their cash flow expectations. In such a setting, distinguishing between rational and behavioral channels requires the observability of marginal investors' beliefs, not just analysts' beliefs.

[4]Throughout the paper, I use two versions of cash profitability corresponding to Ball, Gerakos, Linnainmaa, and Nikolaev (2016) and Fama and French (2018), referred to as cash-based-operating profitability (CBOP) and cash profitability (CP) respectively. Both measures adjust for accruals but differ in that CP subtracts net interest expense and is scaled by lagged book equity, whereas CBOP does not subtract interest expense and is scaled by lagged total assets. In the introduction, I only discuss results from CP but in the body of the paper, I present results from both versions.

0.22% for the benchmark case to 0.69% for expected profitability. And the monthly return differences for the interquartile range of profitability rise from 0.05% for current profitability to 0.12% for expected profitability. Value-weighted regressions generate similar increases in average slopes, suggesting that the improvements in return premia are not concentrated in small stocks.

To the best of my knowledge, there are three other studies that examine the relation between variables that are similar to (but not exactly the same as) past profitability growth and expected profitability. Akbas, Jiang, and Koch (2017) study the "trend" in quarterly profitability growth extracted from firm-by-firm regressions with eight observations. They report that this trend variable is positively related to future profitability and returns. Aside from the statistical issues with extracting information from regressions with three degrees of freedom, the trend variable is linear, deterministic, and assumes a constant rate of change. As such, it restricts the data from speaking to reversion in the growth of profitability. As described earlier, Bouchaud, Krueger, Landier, and Thesmar (2019) model sticky expectations to explain the profitability "anomaly", so their purpose is quite different from mine. But in one of their tests, they estimate persistence in profitability levels (not growth) using firm-level time series regressions that require 11 annual observations. They report that factor model intercepts are higher for portfolios with higher profitability persistence. I conduct a simulation exercise and show that such data requirements generate survivorship bias which obscures reversion. Finally, Lim, Sotes-Paladino, Wang, and Yao (2024) assume that persistence of profitability growth (not levels) can be used to measure expected profitability and report that future returns are positively related to profitability growth. That is counter to the evidence in Fama and French (2000), the partial adjustment models that I estimate, as well as some of their own regression evidence. I provide a fuller discussion and reconciliation of these studies in Section 4.5. However, another way to confront the discordance in results and gauge the robustness of the cross-sectional approach is to conduct out-of-sample tests. This has the added advantage of guarding against inadvertent data snooping in the oft-studied US data (despite the fact that the investigation is guided by well-established financial theory).

I conduct two out-of-sample tests. The first is rarely studied US data between 1940 and 1974. Here too past profitability growth negatively predicts future profitability and the incremental increase in explanatory power of the regressions is similar to the 1975-2024 period. In return regressions, the average slopes on past profitability growth are also negative, similar to the 1975-2024 period. Measures of expected profitability that incorporate past profitability growth continue to have substantially larger average return premia. For example, the average slope on current profitability in this early sample period is 0.28% but

rises to 0.74% for expected profitability.

The second out-of-sample test considers international stocks from both developed and emerging markets. I study more than 10,000 stocks from 41 countries between 1991 and 2024. Once again, past profitability growth has incremental explanatory power in predicting future profitability with average slopes that are consistently negative. In the return regressions, the average slopes on past profitability growth are also negative. And while the average return premia associated with current profitability is 0.20%, it more than doubles to 0.45% when using expected profitability. Finally, to assess if results from such a large cross-section of firms might be driven by extremes, I restrict the sample to firms above the 90th percentile in the distribution of market capitalization, about 1,500 firms per year. This corresponds to the large size breakpoint used by Fama and French (2012) and roughly mimics the composition of the MSCI ACWI ex-US index. The improvement in return premia in this highly restricted sample is larger – the average slope on current profitability is 0.12% but rises to 0.56% using expected profitability.

The remainder of the paper is organized as follows. Section 2 describes sample construction for both the main sample as well as the out-of-sample tests. Section 3 contains regressions that forecast future profitability and future profitability growth. Return evidence from regressions and portfolios sorts are in Section 4, and out-of-sample evidence is in Section 5. Section 6 concludes.

2 Data and Measurement Details

2.1 Main Sample

The sample is constructed from all NYSE, Amex, and Nasdaq firms with share codes 10 and 11 from the CRSP-Compustat Merged Database using LinkTypes `LC` and `LU`, and requiring that the fiscal period end date be within the link date range. The main sample excludes financials and utilities, for the period 1975-2024. The regressions use either all eligible firms, or are restricted to all-but-microcaps (defined as stocks with market value of equity above the 20th percentile of NYSE market capitalization).

Measurement of most variables (e.g., book-to-market ratios) follows the existing literature. There are, however, some important variants specific to profitability (Y_t) and expected profitability. The early literature often uses earnings or cash flow as a measure of profitability with mixed success (e.g. Lakonishok, Shleifer, and Vishny (1994), Fama and French (1995)). Novy-Marx (2013) makes a strong case for gross profitability, and Fama and French (2015) follow up with operating profitability. Accruals can potentially generate reversals in

measured profitability and can also be tied to returns (Sloan (1996)). Ball, Gerakos, Linnainmaa, and Nikolaev (2016) argue that operating profitability cleansed of accruals dominates all other measures in spanning tests, and Fama and French (2018) provide confirmatory evidence. However, the state-of-the-art versions of cash profitability used by these authors differ in construction and scaling. Following Ball, Gerakos, Linnainmaa, and Nikolaev (2016), I construct cash-based operating profitability (CBOP) as sales minus cost of goods sold minus SG&A (net of R&D), with accrual adjustments following the balance sheet method described in their paper. CP is the Fama and French (2018) version of cash profitability, which is sales less the sum of cost of goods sold, net interest expense, and SG&A, and with the same accrual adjustment. CBOP is thus a firm-level measure, whereas CP represents an equity-level flow. Accordingly, CBOP is scaled by lagged total assets, while CP is scaled by lagged book equity (for evidence on why the consistency of the deflator matters, see Ball, Gerakos, Linnainmaa, and Nikolaev (2015)). To be consistent with these scalar, in regressions that use CBOP, I measure investment as the percentage change in assets from t-2 to t-1 (dA_{t-1}/A_{t-2}), but use the percentage change in book equity (dB_{t-1}/B_{t-2}) for regressions that use CP. Appendix A contains Compustat variable definitions for construction of the profitability variables.

The timing convention is as follows. For annual regressions that use future profitability ($Y_{t+\tau}$) as a regressand, I refer to year t as current or prevailing profitability, and $t-l$ as lagged profitability. Past profitability growth (ΔY_t) is the level difference in profitability between t and $t-1$. In monthly return regressions, returns are measured from July through June of $t+1$ and regressors are from year t, requiring a minimum separation of six months to observe accounting data. The accounting data are from fiscal year t-2 to to calendar year t-1 so that information is observable well before returns. Such separation is particularly important for the 1940-1975 sample period (described below) in which the lag between the publication of accounting information and its availability to investors could involve significant delays.

2.2 The Pre-1975 Sample

I construct a sample from 1940 to 1975 as follows. I use historical book values from Ken French's website to construct book-to-market ratios (Davis, Fama, and French (2000)). For profitability and investment variables, I use the data in Wahal (2019). The time series starts in 1938 because prior to that the accounting data are quite poor; consistent accounting standards appear after the 1937 partnership between various Accounting bodies and the Securities and Exchange Commission, which was established in 1934. Because two years of accounting data are required to measure the investment variables, the sample effectively starts in 1940. In addition, information on accruals is not available for this sample period.

Therefore, I construct two versions of operating profitability corresponding to CBOP and CP (i.e., including and excluding interest expense respectively) but without the accrual adjustment. As before, these operating profitability measures are scaled by lagged assets and lagged book equity respectively.

2.3 The International Sample

The sample of international stocks is from Compustat. Canadian securities are from Compustat North America, and other non-US securities are from Compustat Global. The sample includes 41 countries that constitute the bulk of the MSCI All Country World Index ex-US (ACWI ex-US) over this period.[5] The data cleansing and variable construction process mostly follows Bessembinder, Chen, Choi, and Wei (2023). In general, variables are constructed similarly to the main sample, but account for slight differences in constituent data items, details of which are described in Appendix B. All local currency data are converted to US dollar equivalents using exchange rates from Compustat.

The international sample starts in 1991 and contains a large number of stocks, similar to the number of stocks reported in portfolio statistics on Ken French's website.[6] As of June 2024, the 2×3 size and book-to-market portfolios on Ken French's website contain about 33,000 stocks (16,281 firms in developed markets including the U.S., and 17,376 firms in emerging markets). In my sample, the number of firms with valid size and book-to-market ratios (excluding the US) in the same month is 27,064. The size distribution of these securities is highly skewed; a large fraction of stocks have very low market capitalization, especially in countries like China and India that have multiple stock exchanges. To ensure that tiny stocks do not dominate the sample, I only keep firms above the 25th percentile in the distribution of USD market capitalization as of each June. This is compositionally similar to an "all-but-microcap" sample for US stocks.

Even with such restrictions, there remain a large number of small stocks. For robustness tests, I also construct a sample in which I only keep stocks above the 90th percentile in the distribution of market capitalization each June, which corresponds to the Fama and French (2012) definition of large stocks. The average number of stocks per year for this restricted sample is 1,522, similar to the MSCI ACWI ex-US index which has 1,983 firms that represent 85% of the global ex-US market capitalization.

[5]The country composition of the MSCI ACWI ex-US index changes over the time series when countries are added (e.g., Kuwait in 2020) and removed (e.g., Argentina in 2021).

[6]The data on Ken French's website are derived from a combination of International Finance Corporation and Bloomberg.

3 Expected Profitability

3.1 Future Profitability Regressions

The first step in developing a proxy for expected profitability is to estimate annual cross-sectional regressions predicting future profitability. Early studies estimate time series models but these have largely been abandoned because data requirements can introduce biases, and because of power considerations (see, for example, Freeman, Ohlson, and Penman (1982)). To estimate autocorrelations, one would need a reasonable time series of accounting data. Imposing such a requirement would likely introduce significant survivorship bias, particularly since the median life of a security in the CRSP database is only 7 years (Bessembinder (2018)). In addition to avoiding these pitfalls, another advantage of the cross-sectional approach is that it naturally addresses concerns about the correlation of residuals across firms arising from common shocks to profitability.

Procedurally, I follow the approach of Fama and French (2006) but with the important modification that the regressions are estimated at the firm level and not on a per-share basis (Aharoni, Grundy, and Zeng (2013)). The annual regressions take the following form.

$$Y_{t+\tau} = \alpha + \sum_{l=0}^{2} \beta_l Y_{t-l} + \gamma Z_t + \epsilon_{t+\tau} \tag{1}$$

where profitability is forecast up to three years into the future ($\tau = 1, 2, 3$). Z_t consists of a standard set of control variables that include the logarithm of book-to-market ratios, the logarithm of market equity and one of the two measures of investment ((dA_{t-1}/A_{t-2}) or (dB_{t-1}/B_{t-2})). I do not include measures of accruals as regressors because the profitability measures are already cleansed of accruals. I consider several lags of profitability, corresponding to $l = 0$, 1, and 2. The regressions are estimated annually on the all-but-microcap sample, excluding financials and utilities but I can report that the results are very similar for all stocks. All explanatory variables are winsorized at the 1% and 99% level.

Table 1 reports average slopes and t-statistics for the three forecast horizons. Panels A and B correspond to CBOP and CP respectively. Book-to-market ratios and investment are negatively related to future profitability, and firm size is positively related to future profitability. Since these confirm previously documented results, I do not dwell on them further except to note that they play a role in subsequent second-stage regressions that explain future returns.

The first column of the table shows a baseline specification which uses profitability in year t to predict profitability in year t+1. Using CBOP (CP), the average slope for Y_t is 0.559

(0.276) with a t-statistic of 27.28 (11.82). The positive average slopes indicate persistence in profitability, which provide the foundation for using current profitability as a proxy for expected profitability. But the regressions also contain evidence of mean reversion. First, the average slopes for Y_t decrease as the forecast horizon increases. For example, in Panel A, the average slopes drop to 0.461 and 0.413 in the second (τ=2) and third (τ=3) year. Second, the average slopes on Y_t are reliably different from 1.0. For the one year ahead forecast, for example, the t-statistics for whether the average slopes on Y_t using CBOP and CP are different from 1.0 are 21.53 and 31.44 respectively.

The second column adds two lags of profitability ($l = 1, 2$). The average slopes on Y_t drop relative to specifications that do not include lagged profitability, and the average slopes on Y_{t-1} and Y_{t-2} are positive. Using CBOP, the average slope on Y_t drops to 0.404 (compared to 0.559 in the first column), and the average slopes on Y_{t-1} and Y_{t-2} are 0.160 (t-statistic = 20.21) and 0.115 (t-statistic = 14.24). Notably, the average adjusted-R^2 rises from 0.44 in the first column to 0.49 with the addition of lagged profitability; the partial R^2 (using the average adjusted-R^2 across all years) is 9% indicating an economically significant increase in previously unexplained variation in future profitability. The coefficients on book-to-market ratios, market equity and investment are mostly unchanged, implying that the increased explanatory power comes from lagged values of Y_t and is not at the expense of other variables.

These results are in stark contrast to Fama and French (2006, pg. 501) who write "Without showing the details, we can report that adding more lags of profitability, or replacing the first lag with a three-year average, does *not* produce stronger evidence for the importance of lagged profitability in predicting future profitability than the first lag of profitability alone" (emphasis added).[7] To check whether sampling differences are responsible for this discordance, I also estimate regressions for their sample period, 1977-2003. Using CP, which corresponds to their scaling of profitability by book equity, the coefficients on Y_{t-1} and Y_{t-2} are 0.115 (t-statistic = 13.91) and 0.105 (t-statistic = 8.79) respectively. This suggests that their inferences may have been influenced by their use of per-share variables.[8]

In the third column of each panel, I replace lags of profitability with their level difference, ΔY_t. This represents the lags in a more economically interesting manner as past growth in

[7] To disambiguate, the first lag in their regressions corresponds to profitability in t in my specifications.

[8] See Aharoni, Grundy, and Zeng (2013) for an explanation of why firm-level variables are appropriate over per-share level variables.

profitability is a transformation of lags in profitability ($\Delta Y_t = Y_t - Y_{t-1}$).[9]

$$Y_{t+\tau} = \alpha + \beta_1 Y_t + \beta_2 \Delta Y_t + \gamma Z_t + \epsilon_{t+\tau}, \tag{2}$$

As before, the average adjusted-R^2 is higher than the baseline model in both panels, confirming the incremental explanatory power generated by past profitability growth. In Panel A (B), the average slope on ΔY_t is -0.201 (-0.107) with a t-statistic of 29.04 (8.67). Since Y_t and ΔY_t have different units, their magnitudes are not directly comparable. Therefore, I also estimate versions of these regressions after standardizing the variables in each year. The results are not reported in a table but easily summarized: using CBOP, the average slopes on Y_t and ΔY_t are 0.66 and -0.19, suggesting that mean reversion attenuates the effects of persistence by about 28 percent ($\frac{0.19}{0.66}$). Using CP, the average standardized slopes on Y_t and ΔY_t are 0.36 and -0.15 respectively, so that the attenuation is almost 40%.

By both metrics, incremental explanatory power and the magnitude of the coefficients, it is clear that past profitability growth contains information about future profitability, suggesting partial adjustment. Despite persistence in the level of profitability, the coefficients suggest a degree of mean reversion, which is examined further below.

3.2 Partial Adjustment Models

Table 2 starts with annual univariate cross-sectional regressions of ΔY_{t+1} on ΔY_t. The average slope on ΔY_t is approximately -0.35 using both CBOP and CP, implying that about 35% of the change in profitability is reversed in the following year.[10] Adding the prior level of profitability (Y_t) to the regression, the average adjusted-R^2 in the CBOP (CP) regression rises from 0.14 (0.18) to 0.25 (0.38) indicating that both the level and past growth in profitability matter for future profitability growth. The negative average slope on Y_t implies that firms with high levels of profitability experience lower future profitability growth; the rate of mean reversion is about 30% using CBOP and 64% using CP. As expected, this reduces the average slope on ΔY_t to -0.212 for CBOP and -0.100 for CP, but both slopes are still reliably different from zero with t-statistics of 20.59 and 7.63 respectively.

[9] The coefficient on Y_t in equation (1) is the sum of β_1 and β_2 in equation (2) and the coefficient on Y_{t-1} in equation (1) is β_2 in equation (2).

[10] To my knowledge, the first investigation of whether future profitability growth depends on past profitability growth is Little (1962). He reports no correlation between the two. There are numerous subsequent investigations, mostly using time series approaches that are subject to statistical issues. An important exception is Fama and French (2000) who advocate for the cross-sectional models that I use here.

The dynamic component of the classic partial adjustment model is

$$\Delta Y_t = \lambda(\hat{Y}_t - Y_{t-1}) \tag{3}$$

where the partial adjustment coefficient is λ, such that $0 < \lambda < 1$. Similar to Fama and French (2000), I estimate an unconstrained version of the model which uses fitted values of first stage regressions in Equation 1 (equivalent to the first column in Table 1), to compute $\hat{Y}_t$. The fitted values agglomerate information in size, book-to-market ratios, investment, and past profitability into expected profitability. The third column shows that adding $\hat{Y}_t$ to the regressions raises the average adjusted-R^2 from 0.25 to 0.29 in the CBOP regression and from 0.38 to 0.44 in the CP specification. For both profitability measures, the average slope on $\hat{Y}_t$ is positive and close to the negative average slope on Y_t. But, even with the partial adjustment term, the average slope on ΔY_t remains quite large: using CBOP (CP), the average slope on ΔY_t is -0.194 (-0.097) with a t-statistic of 28.19 (9.02), indicating larger reversals in profitability beyond those captured by the partial adjustment model.

A simple economic explanation for mean reversion in profitability is one in which competition acts as the agent of change. Highly profitable firms attract competition which generates mean reversion in profitability, and highly unprofitable firms invite bidders who redeploy assets and strive to increase future profitability. It is interesting to ask whether this dynamic has changed over the time series for at least two reasons. First, the industrial organization literature is concerned with increased monopolistic or oligopolistic behavior which can reduce mean reversion in profitability. Second, the market for corporate control has waxed and waned over the time series, which can also generate differential levels of mean reversion. Figure 1 shows the time series of parameter estimates for ΔY_t, Y_t, and $\hat{Y}_t$ from the partial adjustment model. The top panel displays estimates using CBOP while the bottom panel shows estimates using CP. While the annual coefficients bounce around somewhat, there are no striking departures from the time-series mean, implying considerable consistency in the forces of competition.

4 Expected Returns

4.1 Estimation Considerations

The evidence that past profitability growth predicts future profitability may, but need not, imply predictive power for returns through the expected profitability channel. Any empirical investigation of incremental predictive power for returns is handicapped by the methodolog-

ical complications highlighted by Fama and French (2008) and described as the "multidimensional challenge" to asset pricing by Cochrane (2011). A long literature emphasizes that valuation ratios embed both expected cash flow growth and expected returns, which means that any investigation of the incremental usefulness of past profitability growth in describing expected profitability must account for expected growth already built into valuation ratios. In the Fama and French (2006, 2015) incarnation of the dividend discount model, expected returns are determined by the joint distribution of expected profitability, expected investment, and book-to-market ratios. In Vuolteenaho (2002), expected profitability determines discount rates but varies with firm size. In production-based models, expected profitability, expected investment, and firm size (through variation in adjustment costs) determine expected returns. In addition to the demands of theory, from an empirical perspective, large firms are more profitable than small firms, and low book-to-market firms are more profitable than high book-to-market firms. Adding past profitability growth to this already multi-dimensional picture complicates things further because all of these variables have to be controlled for: in the language of Cochrane (2011, pg. 1601) "we cannot chop portfolios 27 ways". That makes portfolio-based time-series tests infeasible, or at least dubious.

Given these issues, I use Fama and MacBeth (1973) regressions. The benefits are manifold. First, the regressions generate direct estimates of marginal effects associated with past profitability growth, and permit tests against a specific alternate hypothesis (i.e., that current profitability is a sufficient statistic for measuring expected profitability). Second, t-statistics allow for multicollinearity in the explanatory variables and cross-sectional covariance in the residuals without formal estimation (Fama (2015)). That is important, given the aforementioned dimensionality problem. Third, first-stage regressions allow me to generate proxies for expected profitability and compare their relevance for future returns. This is useful because the units for expected profitability are the same as current profitability, permitting direct comparisons of average slopes. Moreover, the regressions use individual stock-level estimates of expected profitability, rather than burying them in diversified portfolios. Finally, since the technology is so well established, it emphasizes economic content over method.

The regression approach is not without tradeoffs. Most importantly, estimates can be driven by microcap firms of limited economic importance. I get around that by also estimating specifications for all-but-microcap firms and by estimating value-weighted regressions. In addition, the regressions are beholden to functional forms, but this is what gives them the power to distinguish the return effects of current profitability from past profitability growth. I do, however, explore non-linearities within the same framework. Finally, and despite the aforementioned misgivings, I use portfolio sorts in Section 4.3, mostly as a sanity check.

4.2 Profitability, Past Profitability Growth, and Returns

Table 3 reports average regression slopes of monthly returns on profitability, lagged profitability, and past profitability growth. The regressions also include the logarithm of the book-to-market ratio, the logarithm of the market value of equity, prior month returns ($R_{1,1}$), prior 11 month returns ($R_{2,12}$), and investment. As before, the investment measures dA_{t-1}/A_{t-2} and dB_{t-1}/B_{t-2} correspond to the use of CBOP and CP. The regressions are estimated using data from July 1975 to December 2024. Panels A and B use all stocks and all-but-microcap stocks respectively. All slopes are multiplied by 100. The usual interpretation applies: the average slope on a variable represents the average return to a zero-cost portfolio with unit exposure to the variable and zero exposure to all other variables. The t-statistic (the average slope divided by its time series standard error) is equal to the annualized Sharpe ratio times $\sqrt{T}$, where T=49, the number of years in the sample (Ball, Gerakos, Linnainmaa, and Nikolaev (2015)).

The average slopes for book-to-market ratios, market equity, investment, and prior returns are similar to those reported by prior studies and I do not discuss them further. For each profitability measure, the first regression in each panel serves as a benchmark case because it only includes current profitability (in addition to the control variables). Consistent with the extant literature, Y_t is positively related to future returns. In Panel A, the average slope of Y_t using CBOP is 1.86% with a t-statistic of 9.27. In comparison, Ball, Gerakos, Linnainmaa, and Nikolaev (2016) report an average slope of 2.60% with a t-statistic of 9.69 over the 1963-2014 sample period. Using CP, the average slope is 0.29% with a t-statistic of 5.55.

The second column for each measure adds Y_{t-1}. There is some diminution in the average slopes for Y_t, but more importantly, the average slopes for Y_{t-1} are positive and statistically significant. Using CBOP (CP), the average slope on Y_{t-1} is 0.64% (0.15%) with a t-statistic of 3.69 (3.16). The third column uses ΔY_t. Consistent with the smaller average slopes on lagged profitability, the average slopes on past profitability growth are negative: using CBOP, the average slope on ΔY_t is -0.51% and for CP, the average slope is -0.10%. The associated t-statistics of 3.01 and 2.81 on the two variants ΔY_t are notable because of the Sharpe Ratio interpretation; they are similar in magnitude to those on Ln(B/M) and Ln(ME), and larger than those on $R_{2,12}$, underlining the economic importance of past profitability growth.

Panel B contains identical specifications using the all-but-microcap sample. The average number of stocks in each cross-section decreases from about 2,500 to 1,138. Using CBOP, the average slope on Y_t is now 1.33%, compared to 1.86% in Panel A, but still reliably different from zero. The decline in the average slope for CP from Panel A to Panel B is

miniscule, from 0.29% to 0.26%. And there is very little change in the slopes on Y_{t-1} or ΔY_t compared to the Panel A. In short, there is robust evidence that changes in past profitability convey additional information about future stock returns beyond that contained in the level of profitability.

In Table 4, I investigate non-linearity in two ways. I first augment the return regressions in Table 3 by including an interaction term between the level of profitability and past growth in profitability ($Y_t \times \Delta Y_t$). The average slopes on Y_t and ΔY_t remain similar to those in Table 3. But the slopes on the interaction term are negative. For the all stock sample in Panel A, the average slopes on $Y_t \times \Delta Y_t$ are -1.63% (t-statistic = 4.22) and -0.04% (t-statistic = 2.32) using CBOP and CP respectively. In the all-but-microcap sample, the magnitude of the average slopes are similar (-1.80% and -0.05%) but with somewhat larger standard errors (the t-statistics for the CBOP and CP specifications are 2.68 and 1.85 respectively). The negative coefficient on the interaction term reveals an important aspect of the relationship between profitability and future returns: the positive relationship between profitability and future returns is weaker for firms that have recently experienced increases in profitability. In other words, high profitability predicts higher returns, but this predictive relationship is attenuated when profitability has been recently growing.

To investigate asymmetry between low and high profitability levels, I also estimate regressions with a second type of interaction effect. Each June, I sort firms into profitability quintiles based on NYSE breakpoints. I then interact past profitability growth with indicator variables corresponding to high and low profitability quintile assignments: $\Delta Y_t \times$HighProf and $\Delta Y_t \times$LowProf.[11] The average slopes on these variables assess how past profitability growth is related to future returns for high and low profitability firms, while the slope on ΔY_t corresponds to the intermediate quintiles. In both panels, the average slope on ΔY_t is substantially reduced and the average slopes on $\Delta Y_t \times$LowProf are indistinguishable from zero. However, the average slope on $\Delta Y_t \times$HighProf is negative, suggesting that much of the attenuation in the returns associated with profitability is coming from high profitability firms which also have high past profitability growth.

4.3 Portfolio Sorts

Notwithstanding the constraints associated with sorts described in Section 4.1, it is also of interest to assess portfolio returns and time-series factor models, particularly if one re-

[11] The low profitability quintile has negative profitability on average but for convenience, I continue to refer to it as LowProf.

gards the factors as capturing systematic risk.[12] In an unconstrained setting, portfolio sorts would be on size, investment, a valuation ratio such as book-to-market, profitability, and past profitability growth. That would control for co-determined variables and isolate the incremental influence of profitability growth holding other variables roughly constant. Since sorts on five variables are not feasible, I adapt the portfolio approach to accommodate this multidimensionality. Each June, stocks are independently ranked on book-to-market ratios, profitability, size, and investment (i.e., an independent rank transform). The size and investment rankings are in descending order to preserve the directional relation with expected returns. Using the average rank across these variables, each stock is then assigned a composite rank quintile. On average, each composite rank quintile contains approximately 500 stocks. Within each quintile, stocks are further sorted into past profitability growth quintiles (i.e., conditional ΔY_t quintiles). The first sort roughly holds constant expected returns derived from size, book-to-market ratios, investment, and profitability.[13] The second sort examines variation in returns that might come from past profitability growth, holding other determinants roughly constant. Portfolios are rebalanced annually, and value-weighted returns are computed from July to June of the following year.

Panels A and D of Table 5 report average monthly excess returns for the 5x5 portfolios using CBOP and CP respectively.[14] There are two ways to examine the dispersion in excess returns. One can hold the past profitability growth quintiles constant and examine variation in excess returns across the composite rank quintiles, looking vertically down each column. In doing so, the penultimate row in each panel shows the return spread between high and low composite rank portfolios with t-statistics in parentheses. In the first four columns (i.e., ΔY_t quintiles Low through 4), there is a monotonic increase in excess returns: the high-minus-low return spreads are consistently positive with large t-statistics. That is by construction since the composite rank quintiles are essentially sorts on expected returns generated by the ranking variables. But there is no such increase in returns for the high ΔY_t quintile. The high-minus-low return spread for the high ΔY_t quintile using CBOP (CP) is -0.11 (-0.01)

[12] A clarification and distinction is in order. Fama-MacBeth regressions can be viewed as cross-sectional factor models and are perhaps better than time-series factor models at explaining the cross-section of returns (see Fama and French (2020)). A fuller discussion is deferred to Section 4.4.

[13] The composite ranking approach is not without limitations. It cannot use NYSE breakpoints, it assigns equal weight to each of the variables, and loses the correlation structure between variables. It is, however, arguably better than ignoring important information in these variables, as would be the case in sorts on pairs of variables or even triplets.

[14] I do not show portfolio characteristics in a table to conserve space but they reflect the portfolio construction procedure. There is monotonic variation in weighted average size, book-to-market ratios, and profitability across the composite rank quintiles and minimal variation in each of these characteristics across ΔY_t quintiles. The weighted average past profitability growth is negative for the low ΔY_t quintile, rising steadily for the remaining ΔY_t quintiles.

with a t-statistic of 0.48 (0.01), implying that high past profitability growth significantly dulls the impact of the other variables.

A second way to examine dispersion is to hold the composite rank quintiles constant and look at excess returns across the ΔY_t quintiles (i.e., horizontally, from left to right). Here too the nonlinearities become apparent. In the low composite rank quintile, the difference in average monthly excess returns between high and low ΔY_t quintiles is 0.32% (t-statistic = 2.00) for CBOP and 0.17% for CP (t-statistic = 1.00). But in the high composite rank quintile, these return differences are sharply negative, -0.60% (t-statistic = 3.42) for CBOP and -0.45% (t-statistic = 1.89) for CP, consistent with the negative average slope on $\Delta Y_t \times$ HighProf in the regressions in Table 4.

Given the variables used to construct the composite rank, factors constructed from the same underlying variables should price these 5x5 portfolios.[15] Panels B (CBOP) and E (CP) show intercepts from time series regressions of portfolio returns on the five-factor model (Panels C and F contain corresponding t-statistics). The time-series five-factor model has difficulty pricing extreme portfolios. The intercept for the low composite rank and high ΔY_t portfolio is 0.50% using CBOP and 0.27% using CP, with t-statistics of 3.95 and 2.62 respectively. And the intercepts of the high composite rank and low ΔY_t are 0.54% and 0.33% with t-statistics of 3.75 and 1.77 respectively.

Hedge portfolios (high-minus-low) within each composite quintile rank also highlight nonlinearity and asymmetry. Using CBOP (CP), the difference in intercepts between high and low ΔY_t portfolios for the low composite rank quintile is 0.37% (0.25%) with a t-statistic of 2.25 (1.69). In the intermediate composite rank quintiles (i.e., quintiles 2, 3, and 4), the spreads between high and low ΔY_t portfolios are small and statistically indistinguishable from zero. In the high composite rank quintile, however, the difference in intercepts of the high and low ΔY_t portfolios are -0.68% (t-statistic = 3.75) using CBOP and -0.64% (t-statistic = 2.42) using CP.[16]

Why are the intercepts for the extreme portfolios and for the hedge portfolios non-zero in the factor models? RMW, the time-series factor meant to incorporate expected profitability

[15] With the caveat that the time-series factors are constructed in specific ways. One could use different factors, or construct the same factors differently, which would generate an entirely different set of factor model intercepts. For instance, one could include a momentum factor or construct HML differently. I avoid such a factor-mining exercise and stick to the Fama and French (2015) factors but note that the Fama and MacBeth (1973) regressions in Table 3 do include prior returns.

[16] The sample excludes financial firms because of their regulartory burdens, "specialness", and accounting complexities. However, the financial sector is a large fraction of the aggregate market and ignoring it could be a meaningful omission; at the end of the sample period (2024), financials represent almost 15% of the S&P500 and of the Russell 3000. I replicate portfolio sorts after including financials; the excess returns and intercepts are only a few basis points apart from those reported in tables.

is based on sorts of current, not expected, profitability. Since past profitability growth contains information for future profitability and is negatively related to future returns, non-zero intercepts reflect the fact that current profitability is an imperfect proxy for expected profitability.

4.4 Expected Profitability and Returns

The evidence thus far shows that controlling for the level of profitability, past profitability growth is negatively related to future returns. As is usual with these kinds of variables, there are several non-mutually exclusive explanations. The present value approach fixates on expected profitability. It suggests that holding prices constant, firms with high current profitability and high past profitability growth should have lower future returns because mean reversion in profitability implies lower future profitability. The behavioral explanation requires biased expectations. One alternative is that investors excessively extrapolate past profitability growth. If so, firms with high past profitability growth should have low future returns and assuming symmetry, firms with low or negative past profitability growth should have high future returns. Another alternative is one of sticky expectations, which implies that firms with high profitability levels and high past profitability growth should have high future returns.

Thus far, the evidence to disentangle these explanations is mixed. The regressions in Table 4 and the portfolio returns in Table 5 show that the combination of high profitability and high profitability growth is negatively related to future returns, consistent with both the present value approach as well as extrapolation. But the regressions contain no evidence that the combination of low profitability and high profitability growth is related to returns; on the other hand, the portfolio results suggest a positive relation between past profitability growth and returns for low profitability firms. A natural way to generate some traction between explanations is to measure expected profitability in ways that align with their underlying logic. For the present value approach, I measure expected profitability using fitted values from the predictive regressions in Table 1, and for the behavioral approach I use analyst expectations to measure expected growth rates and apply them to current profitability to get an estimate of expected profitability. These tests are described below.

4.4.1 Expected Profitability and Investor Expectations

I examine expected profitability using analysts' forecasts. This approach is conceptually aligned with the methodologies of Bouchaud, Krueger, Landier, and Thesmar (2019), Bordalo, Gennaioli, La Porta, and Shleifer (2024), and La Porta (1996), who employ analysts'

forecasts to distinguish expectational errors from rational pricing. Under the widely used premise that analysts' expectations reflect those of marginal investors, one can compute expected profitability for the subsequent period using analysts' forecasts and examine whether expected profitability is related to future stock returns.

There are several empirical challenges. Some analysts provide forecasts of operating profitability but the data field (denoted `OPR`) in the IBES database is sparse. Since the consistency and frequency of one year ahead EPS forecasts are the most populated element of the database, I use them to generate a measure of expected profitability. Specifically, I multiply Y_t by the implied annualized growth rate in EPS forecasts as:

$$\hat{Y}^I_{t+1|t} = Y_t \times \frac{\widehat{EPS}_{t+1}}{EPS_t} \tag{4}$$

where $\widehat{EPS}_{t+1}$ is either the mean or median one year ahead forecast (`FY1`) from the Unadjusted Summary Statistics File, EPS_t is the prior period realized EPS, and the superscript I denotes that the expectation is derived using IBES forecasts. I require that at least three analysts provide EPS forecasts and ensure that there is a minimum of six months between the EPS forecast date (`statsper`) and the end of the fiscal period for which the forecast applies (`fpedats`). Growth rates are only calculable if EPS_t is positive. Since there can be multiple forecast updates, I keep only the most recent forecast prior to June of each year, so that forecasts are available prior to the return evaluation period.

Table 6 reports average slopes from return regressions that use $\hat{Y}^I_{t+1|t}$. The average number of stocks in the cross-section is 986, substantially lower than the 2,541 stocks in Panel A of Table 3, but close to the all-but-microcap sample in Panel B of the same table. The smaller cross-section is because analyst coverage of small stocks is limited. To ensure that such data-related sampling issues do not drive inferences, I first replicate the baseline return regressions in Table 3 with this smaller sample. Columns (1) and (3) show that the average slopes on Y_t are positive and comparable to previous estimates, alleviating such concerns.

The main regressions appear in columns 2-3 and 5-6 which use average and median EPS forecasts respectively. In both specifications, the average slope on $\hat{Y}^I_{t+1|t}$ is indistinguishable from zero; there is no evidence that analysts have expectations of future profitability that are extrapolative or sticky. This non-result is, however, consistent with Bordalo, Gennaioli, La Porta, and Shleifer (2024) who report that profitability is the one notable exception to their finding that expectation-based returns explains the cross-sectional variation in realized returns tied to value, investment, size, and momentum. Of course, as is always the case with any measure of expectations, there remains the possibility that measured expectations differ

from the expectations of marginal investors.

4.4.2 Expected Profitability and Linear Projections

The improvement in the description of the data generating process for future profitability in Table 1 suggests that fitted values from such regressions may be a better measure of expected profitability than current profitability (Y_t). I measure expected profitability using fitted values from a first-stage regression that predicts next period profitability using the full set of explanatory variables (Z_t) in Table 1.

$$Y_{t+1} = \alpha + \beta_1 Y_t + \beta_2 \Delta Y_{t,t-1} + \gamma Z_t + \epsilon_{t+1}, \tag{5}$$

Including size, book-to-market ratios, and investment, respects the joint determination of profitability via dividend discount, q-theory, and other models. Including a valuation metric like the book-to-market ratio means that market-implied expected growth rates at time t are built into the fitted values. Cohen, Polk, and Vuolteenaho (2003) report that 75% of the dispersion in book-to-market ratios is explained by expected cash flow growth whereas Delao, Han, and Myers (2025) find that only 25% of the disperison in PE ratios is reflected in differences in future earnings growth. Regardless of the magnitude, the inclusion of a valuation ratio in the first-stage regression adds to its usefulness.

Since the regression are estimated when Y_{t+1} is known, I merge the fitted values with returns in July through the June of the following year to ensure no look ahead bias. For example, if profitability in year t is measured as of June 30, 2000 (which may come from a fiscal year end December 31, 1999), then fitted values are computed as of June 30, 2001. As with other tests, these are merged with returns from July 2001 to June 2002. I use the compact notation of $\hat{Y}_{t+1|t}$ without the I superscript to indicate that expected profitability is derived from the first-stage regression, and to be explicit about the timing convention.

Panel A of Table 7 contains average slopes and t-statistics from return regressions that use current and expected profitability measures for all stocks. The average slopes represent the return premia associated with zero-cost portfolios, and since the measurement units of current and expected profitability are the same, the differences in slopes can be interpreted as increases in premia associated with better measurement of expected profitability. Columns (1) and (4) contain the benchmark case of current profitability as a proxy for expected profitability. The average slope on Y_t is 1.80% (t-statistic = 8.14) for CBOP and 0.34% (t-statistic = 5.04) for CP.[17] Columns (2) and (5) contains regressions that use both Y_t and

[17]These average slopes differ by very small amounts from the baseline regressions in Table 3. That is because estimates of expected profitability require projections from first stage regressions, which slightly

$\hat{Y}_{t+1|t}$, a horse race between the two proxies. Here the average slopes on both Y_t and $\hat{Y}_{t+1|t}$ are positive. The average slopes on Y_t are attenuated, dropping to 1.19% for CBOP and 0.29% for CP. The average slopes on $\hat{Y}_{t+1|t}$ are larger, 1.64% for CBOP and 0.50% for CP, implying that past profitability growth (in addition to other variables) contains incremental information for returns.

Columns (3) and (6) only use expected profitability.[18] The average slopes on $\hat{Y}_{t+1|t}$ are 2.81% and 0.77% using CBOP and CP respectively. These are 56 percent and 226 percent higher than their counterparts using Y_t. Another way to gauge economic significance is to compute the return difference attributable to cross-sectional variation in profitability. Each month, I multiply the estimated coefficient on Y_t or $\hat{Y}_{t+1|t}$ by the inter-quartile range of profitability for that month to generate the expected return difference. The calculation is monthly because the cross-sectional distribution of profitability can shift over time and because the premium associated with it may be time varying. The row labeled "average implied IQR return difference" reports the time series average of these return differences for each column. For CBOP, the average monthly return difference rises from 0.29% using Y_t to 0.35% using $\hat{Y}_{t+1|t}$. The t-statistic of the difference is 2.06. For CP, the increase is even larger, rising from 0.11% for Y_t to 0.21% for $\hat{Y}_{t+1|t}$, with a t-statistic of 2.17.

Panel B contains equivalent estimates for the all-but-microcap sample. Here the increase in return premia associated with expected profitability is often larger than in Panel A. Using CBOP, the premia rises by 71 percent (from 1.22% to 2.09%) and using CP, the increase is 313 percent (from 0.22% to 0.69%). And using the inter-quartile range, the average monthly return difference rises from 0.17% to 0.22% using CBOP and from 0.05% to 0.12% using CP (with t-statistics of 1.80 and 2.01 respectively). These results indicate that inferences are not sensitive by numerous small stocks which represent a small proportion of the aggregate market capitalization. It is also useful to estimate regressions weighted by market capitalization. Table 8 contains such value-weighted Fama-MacBeth regressions using all stocks. The increase in the average slope across various proxies for $\hat{Y}_{t+1|t}$ are similar. Using CBOP, the average slope on $\hat{Y}_{t+1|t}$ rises from 1.08% (t-statistic = 3.30) in the benchmark case to 1.68% (t-statistic = 2.87), an increase of 55 percent. Similarly, using CP, the average slope rises from 0.21% (t-statistic = 2.47) in the benchmark case to 0.40% (t-statistic = 2.02) for $\hat{Y}_{t+1|t}$, an increase of 190 percent.

The Fama and MacBeth (1973) regressions described above can be viewed as cross-sectional factor models that allow constituent factors to compete. In that sense, they test

reduces the time series required for return regressions.

[18]The sum of the slopes on Y_t and $\hat{Y}_{t+1|t}$ in columns 2 and 5 are mechanically equal to the slope on $\hat{Y}_{t+1|t}$ in columns 3 and 6.

for factor redundancy in the same spirit as traditional time-series factor redundancy tests (Fama (2015)). In fact, Fama and French (2020) show that cross-sectional factor models provide a *better* description of average returns than time-series factor models, which suggests that there is inefficiency in forming portfolios based on current and expected profitability and then estimating time-series regressions. Nonetheless, for interested readers, Appendix Table A1 shows that for CBOP, quintile intercept spreads using current profitability based on three-factor models are about 0.59% per month but rise to 0.81% per month using expected profitability. The improvements using CP are, however, only 0.02%.

4.5 Related Studies and Reconciliation

As discussed in the introduction, there are three studies that also examine growth in profitability, either directly or indirectly. They differ from my approach in terms of measurement, methodology, results, and in one case, intent. I discuss each of them below.

Akbas, Jiang, and Koch (2017) use quarterly gross profit (GPQ, scaled by contemporaneous assets) as their profitability measure and estimate the trend in profitability. The slope of their trend variable is measured using the following firm-level rolling-window time series regression estimated using eight observations.

$$GPQ_{iq} = \alpha_{iq} + \beta_{iq}t + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_3 D_3 + \epsilon_{iq}, \tag{6}$$

where t=1,2,...,8, and D represents quarterly dummies to account for seasonality. Each estimate is obtained with just 3 degrees of freedom, implying that the estimates will be noisy. Further, the measured slope is not the same as the difference in profitability over adjacent periods (ΔY_t). They estimate a linear time trend that does not allow for mean reversion. My inclusion of ΔY_t allows the rate of change to vary, an important economic consideration when thinking about the dynamics of profitability in which firms respond to pricing and other changes brought on by competitor behavior.

Bouchaud, Krueger, Landier, and Thesmar (2019) have a purpose that differs from my own – they seek to understand the profitability "anomaly" through the lens of a sticky expectations model. In the last test of their model, however, they report that the returns associated with profitability are larger for stocks with more persistent profits. Their persistence parameter (ρ) is estimated using the following firm-level time series regression.

$$cf_{f,t} = a + \rho.cf_{f,t-1} + \epsilon_{f,t}, \tag{7}$$

where cf is the ratio of operating cash flows to contemporaneous total assets. Table VIII in their paper contains four-factor model intercepts of equal-weighted portfolios based on conditional double sorts, first on profitability persistence (ρ), and then on profitability (or profitability growth). They report that factor model intercepts are higher for firms with more persistent profitability, seemingly at odds with the results in Table 3.[19]

Their approach requires that firms have data for a minimum of 11 years, potentially introducing survivorship issues.[20] I conduct a simulation in which I impose these data requirements on the future profitability regressions in Section 3. The data-generating process for profitability in the simulation is $Y_{t+1} = 0.64 \times Y_t - 0.20 \times \Delta Y_t + \epsilon_t$, which corresponds to the baseline regression estimates in Panel A of Table 1 (I omit the average slopes on the Z_t variables for simplicity). The error term is assumed to be a mean-zero standard normal with a variance of 0.0087, which also corresponds to the variance of residuals in the baseline regression in Table 1 (which has an adjusted-R^2 of 0.48). Y_t is drawn from a normal distribution with a mean of 0.10 and variance of 0.125, equal to the moments from the cross-sectional distribution of profitability in the actual data. In each simulation round, I generate a panel of 3,000 stocks over the 1975-2024 sample period. The population has entry and exit rates of 3%, roughly corresponding to estimates of new listings and attrition rates in the literature (see, for example, Doidge, Karolyi, and Stulz (2017)). To introduce exit rates tied to past profitability, I first calculate average attrition rates for deciles based on average profitability over the prior three years from the actual data. I then use these breakpoints and attrition rates to generate decile-based attrition in the simulated sample. This ensures that poorly performing firms in the simulation face exit rates commensurate with the population. In each simulation round, I then estimate Fama and MacBeth (1973) regressions matching the data generating process as $Y_{t+1} = \beta_1 Y_t + \beta_2 \Delta Y_t + \epsilon_t$, using only firms that survive over the past 10 years.

Figure 2 shows the distribution of β_1 and β_2 from the above regressions across 500 iterations. The red vertical line in each panel shows the true parameters, 0.64 and -0.20 respectively. The upper panel shows that truncation (removal of the left tail) attenuates the estimates of β_1; the median of β_1 in the simulation is 0.54, about 15% below the true value. The bias in β_2 is much larger: the entire mass of the distribution is positive, centered around 0.09 instead of the true value of -0.20. The simulations imply that survivorship bias in time-series approach obscures reversion.

[19] "Seemingly" because my tests also show persistence in profitability levels, in addition to reversion. The major difference is that my tests focus on reversion rather than persistence while using cross-sectional rather than time series methods.

[20] To illustrate the magnitude of the trunction, the regressions in Table 1 contain approximately 1,125 firms per year. If I impose the 11-year requirement, the average number of firms per year drop to 768.

Finally, Lim, Sotes-Paladino, Wang, and Yao (2024) *assume* that profitability growth (not levels) exhibits persistence but no mean reversion, counterfactual to the evidence in Table 2. This assumption in their modeling approach generates the prediction that past profitability growth is positively related to future profitability and returns. They estimate cross-sectional regressions of profitability growth on eight lags and report that the average slopes on the first two lags are positive, which implies persistence.[21] The remainder of their tests are predicated on this evidence. Yet the average slopes at the four and eight quarter lags in these same regressions are significantly negative (with t-statistics of -13.58 and -15.86 respectively), consistent with reversion in profitability growth.

Notwithstanding the above discussion, the differing results may be somewhat disconcerting. One way to gauge the robustness of the evidence is to consider out-of-sample tests. This has the added advantage of addressing widespread concerns with regard to data dredging and p-hacking in the asset pricing literature.

5 Out-of-Sample Evidence

I conduct two out-of-sample tests to assess the veracity of the evidence. The first considers seldom studied data going back to 1940 (exceptions include Linnainmaa and Roberts (2018), Kilic, Yang, and Zhang (2022), and Wahal (2019)). The second repeats tests on a large sample of international stocks from 41 countries.

5.1 Evidence from 1940-1974

5.1.1 Future Profitability Regressions

Table 9 presents regressions of future profitability on lagged variables for the 1940-1974 period, similar to those in Table 1. Even absent adjustments for accruals, the explanatory power of the regressions is higher than those in Table 1. For example, in Panel A of Table 9, the average adj-R^2 of the regressions predicting firm-level operating profitability in t+1 is 0.64, compared to 0.44 for the equivalent specification in Table 1.

Both operating profitability measures show higher persistence for one year ahead forecasts than the more recent sample period: the average slopes on Y_t in Panels A and B are 0.705 and 0.626 respectively, substantially higher than their counterparts in the 1975-2024 period.

[21] Their measure of profitability growth (PG) is $(OP_{i,q} - OP_{i,q-4})/BE_{i,q-4}$, in which the numerator is the difference in two flow variables scaled by a stock variable. In contrast, my measurement of profitability growth is a level difference in a profitability ratio, which addresses the endogeneity between book values and past profits.

As before, the average slopes decline as the forecast horizon increases, and the average slopes on lagged profitability are positive and smaller than those for Y_t. The adjusted-R^2 of regressions that include lagged profitability are also higher than those without lags. For firm-level operating profitability, the addition of lagged profitability raises the adjusted-R^2 from 0.64 to 0.66 and for equity-level operating profitability, the increase is from 0.55 to 0.58.

In regressions that utilize past profitability growth, the increase in explanatory power is somewhat smaller but still positive. In all but one specification, the average slopes ΔY_t are negative. The economic impact of mean reversion seems to be lower in this sample period; in regressions that use standardized variables, the average slopes on firm-level operating profitability and past profitability growth are 0.74 and -0.07 so that the attenuation due to mean reversion is about 10 percent. In general, however, the future profitability regressions for the 1940-1975 period are quite similar to those from the main sample.

5.1.2 Return Regressions

Table 10 contains return regressions for this sample period. Starting with the standard set of explanatory variables, size and prior month returns are negatively related to future returns, mirroring the existing literature for the more recent sample period. Consistent with the evidence in Davis, Fama, and French (2000) and Linnainmaa and Roberts (2018), book-to-market ratios and momentum have positive slopes in the 1940-1974 period. Investment (measured using percentage growth in assets or book equity) is unrelated to average returns, replicating the results in Wahal (2019).

Turning to the average slopes on the profitability variables, column (1) shows that the average slope on Y_t using firm-level operating profitability is 0.81 with a t-statistic of 2.70; using equity-level operating profitability, the average slope is 0.28% with a t-statistic of 1.78. The regressions in column (2) add ΔY_t. The average slopes on Y_t rise to 1.11% and 0.57% but importantly, the slopes of ΔY_t are negative, -1.08% and -0.65%. Thus, in this sample period, past profitability growth is related to future returns in a manner similar to the 1975-2024 period.

Column (3) contains regressions that use both Y_t and $\hat{Y}_{t+1|t}$. Unlike the 1975-2024 sample period, here the average slope on Y_t is indistinguishable from zero and is subsumed by the average slope on $\hat{Y}_{t+1|t}$. Finally, in the last column, the average slopes on $\hat{Y}_{t+1|t}$ show the premium associated with expected profitability. In Panel A, the average slope on $\hat{Y}_{t+1|t}$ is 0.93%, which is 23 percent higher than the average slope on Y_t. In Panel B, the improvement is much larger as the average slope rises from 0.28% using Y_t to 0.74% using $\hat{Y}_{t+1|t}$, a 264

percent increase.

In summary, the basic results obtained from the future profitability and return regressions from the 1975-2024 sample period are replicated in the 1940-1974 period.

5.2 International Evidence

I expect tests that use international data to have low power for at least two reasons. First, the lack of integration between markets may dull competition in the cross-section of firms which may enhance persistence in profitability and reduce mean reversion.[22] Second, variation in accounting standards across countries (such as the use of IFRS) can create measurement problems that could add noise to average slope estimates. Since both issues make it less likely to reject the null, they render the tests below conservative.

5.2.1 Future Profitability Regressions

The international sample is quite large with good coverage across countries over the 1991-2024 sample period. The average number of firms per year is over 10,000, close to those reported by Bessembinder, Chen, Choi, and Wei (2023), and similar to the summary statistics on Ken French's website.

Table 11 contains regressions of future profitability on lagged variables paralleling those in Tables 1 and 9. The average adj-R^2 of the regressions is substantially higher than for the main US sample and comparable to the 1940-1974 sample period. In these regressions, the average slopes on size, book-to-market ratios, and investment are often indistinguishable from zero, suggesting that much of the explanatory power is coming from profitability. For example, in the first column of Panel A, the average slopes on size and book-to-market ratios are not different from zero, and the t-statistic on dA_{t-1}/A_{t-2} is only 2.50. Yet, the average adj-R^2 is 0.61, mostly because the average slope on Y_t is 0.700 (t-statistic = 9.83). Interestingly, this high persistence in profitability in the international sample is comparable to the US in the 1940-1974 sample period (where the average slope on Y_t was 0.705), and much higher than the 1975-2024 sample period (where the average slope on Y_t was 0.559).

In regressions that include lagged profitability, the average slopes on Y_{t-l} are positive and smaller than those for Y_t. Even in this sample, it is clear that past profitability contains information for future profitability. Finally, in all specifications that incorporate past profitability growth, the average slopes on ΔY_t is negative with large t-statistics.

[22] It is well-known from the industrial organization and trade literature that lack of competition created by industrial or trade policy can allow less productive firms to survive and for high profitability firms retain local monopoly power.

5.2.2 Return Regressions

Table 12 contains return regressions for the international sample. The specifications and table formatting are identical to those for the 1940-1974 sample to facilitate back-to-back comparisons. With respect to the control variables, the role of size, investment, and past returns is diminished in this sample. But the average slopes on book-to-market ratios are consistently positive, lining up with the evidence in Fama and French (2012).

In column (1), the average slope on Y_t using CBOP (CP) is 0.75% (0.20%) with a t-statistic of 2.26 (1.81). Adding ΔY_t to the regression in column (2), the average slopes on CBOP and CP rise to 0.96% and 0.29% respectively. The average slopes on ΔY_t are -0.44% and -0.18% but with high standard errors – the corresponding t-statistics are 1.84 and 2.27 respectively. As before, column (3) includes both current and expected profitability. Similar to the 1940-1974 sample period (but different from the 1975-2024 period), expected profitability crowds out current profitability; in both panels the average slopes on Y_t are indistinguishable from zero but the average slopes on $\hat{Y}_{t+1|t}$ are large and positive. Column (4) shows that increases in return premia associated with expected profitability remain large in this sample as well. Using CBOP, the average slope on Y_t is 0.75% but rises by 76 percent to 1.32% for $\hat{Y}_{t+1|t}$. Using CP, the increase is larger, from 0.20% to 0.45%, an increase of 225 percent.

5.2.3 Sampling Issues in International Data

Despite the removal of firms below the 25th percentile of market capitalization, the sample used in Tables 11 and 12 still contains a large number of small firms. As described in Section 2.3, I also study a highly restricted sample of stocks above the 90th percentile of market capitalization that is roughly comparable to the MSCI ACWI ex-US index; on average, the number of stocks in the cross-section is 1,511, compared to the over 10,000 in the earlier international sample. These large capitalization international stocks represent an investable universe for global investors.

In untabulated results from this sample, regressions that predict profitability in $t+1$ are similar to those in Table 11. Using CBOP, the average slope on Y_t is 0.69 (compared to 0.70 in Table 11) with an average adj-R^2 of 0.68. Adding lagged profitability to the regression raises the average adj-R^2 to 0.71 and the coefficients on Y_t, Y_{t-1}, and Y_{t-2} are 0.49, 0.17 and 0.08, comparable to those reported in Table 11. And the specification that uses Y_t and ΔY_t has average slopes of 0.67 and -0.22, close to the slopes of 0.74 and -0.25 in Table 11.

Appendix Table A2 contains average slopes on the profitability related variables from return regressions. Even in this highly restricted sample, the influence of past growth in

profitability is apparent; the average slopes on ΔY_t are -0.72% using CBOP and -0.23% using CP, compared to the -0.44% and -0.18% in Table 12. Unsurprisingly given the size restriction (which is likely correlated with conformity to international accounting conventions), these estimates are also less noisy than those in Table 12 — the corresponding t-statistics are 2.05 and 2.59 respectively. The increase in return premia associated with measures of expected profitability are also comparable. Using CBOP, the average slope on Y_t is 0.67, but the average slope on $\hat{Y}_{t+1|t}$ more than doubles to 2.08%. The increase in average slopes is equally large for CP, rising from 0.12% for Y_t to 0.56% for $\hat{Y}_{t+1|t}$. In short, the return results appear quite robust, even in large international stocks.

6 Conclusion

Expected profitability resides at the heart of present value models. Researchers (and practitioners) take three approaches to estimating the expected stream of future profits: (a) explicitly forecasting cash flow growth rates, (b) allowing for expected profitability to be reflected in current prices and valuation ratios, and (c) using current profitability as a proxy for future profitability. In this paper, I examine the role of past profitability growth in forecasting future profitability. There is strong and robust evidence that past profitability growth negatively forecasts future profitability, consistent with competitive forces in real markets.

I then ask whether past profitability growth contains information for future returns. Past profitability growth is negatively related to future returns, controlling for current valuation (book-to-market ratios), past returns, prior investment, and firm size. Prima facie, the evidence is consistent with both behavioral and present value channels. However, analysts' expectations of expected profitability do not appear to contain information for future returns – to the extent that analyst expectations represent marginal investor return expectations, this lack of evidence weakens the case for the behavioral channel. Finally, I generate a measure of expected profitability that incorporates current profitability, current book-to-market ratios, past investment, firm size, and past profitability growth. This measure of expected profitability has meaningfully larger return premia than current profitability.

Appendices

A US Data and Variable Definition

For the 1975-2024 sample period, the construction of size, book-to-market ratios, investment, and prior returns follows the procedures in Fama and French (1993), Fama and French (2015) and Ball, Gerakos, Linnainmaa, and Nikolaev (2016). The profitability variables are clarified below.

Variable	Definition
Cash-based operating profitability (CBOP)	SALE - COGS - (XSGA - XRD) - Δ[RECT + INVT + XPP − (DRC + DRLT) − AP − XACC]. Scaled by lagged total assets (AT (t-1)).
Cash profitability (CP)	SALE - COGS - XSGA - XINT - Δ[RECT + INVT + XPP − (DRC + DRLT) − AP − XACC]. Scaled by lagged book equity (BE (t-1)).
ΔY_t	(CBOP_t - CBOP_{t-1}) or (CP_t - CP_{t-1})

For the 1940-1975 sample period, the pre-Compustat data for book equity are from Davis, Fama, and French (2000), and the profitability and investment data are from Wahal (2019). These are merged with the post-1950 Compustat data. Since accrual information is not available for this period, the following two operating profitability variables are used.

Variable	Definition
Firm-level operating profitability	[SALE - COGS - (XSGA - XRD)] / AT (t-1).
Equity-level operating profitability	[SALE - COGS - XSGA - XINT] / BE (t-1).

B International Data and Variable Definition

Data collection and cleansing procedures largely follow Bessembinder, Chen, Choi, and Wei (2023) detailed in their Internet Data Appendix. A description of the specifics for the international sample follows.

Primary issues are identified as having an IID code equal to PRIROW. Firms with the following country of incorporation codes (FIC codes) are included in the sample: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Columbia, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, Indonesia, India, Ireland, Israel, Italy, Japan, Korea, Malaysia, Mexico, Netherlands, New Zealand, Norway, Phillipines, Poland, Portugal, Saudi Arabia, Singapore, South Africa, Spain, Switzerland, Taiwan, Thailand, Turkey, Great Britain.

Book equity is calculated as shareholder equity, plus deferred taxes and income tax credits (TXDITC), minus preferred stock. If TXDITC is missing, it is set to zero. For preferred stock, the following preference order is used: PSTKL > PSTK > 0. Missing values of XRD and XINT are set to zero.

For firms with two fiscal year ends, I keep the most recent one. Accurals are computed using the balance sheet method as Δ[RECT + INVT + XPP − XACC]; Compustat variables DRC + DRLT are not used. Cash-based operating profitability and cash profitability are calculated as per the US sample. Accounting variables for each cross-section (across all countries) are winsorized annually at the 1st and 99th percentile.

For all countries except Canada, monthly returns are computed from daily total returns, requiring at least five daily observations with positive prices. If a security has less than six months of monthly returns, the security is dropped entirely. To compute market capitalization, all prices are converted to USD using exchange rates in Compustat Global. Share outstanding are as reported in CSHO in the daily file.

For Canadian firms, returns, shares outstanding, and prices are obtained directly from the monthly file.

The first international sample excludes firms below the 25th percentile in the distribution of USD market capitalization at the end of June. The average size of the cross-section is about 10,000 firms. The second sample excludes firms below the 90th percentile in the distribution of USD market capitalization. The average number of firms per year in this sample is approximately 1,500.

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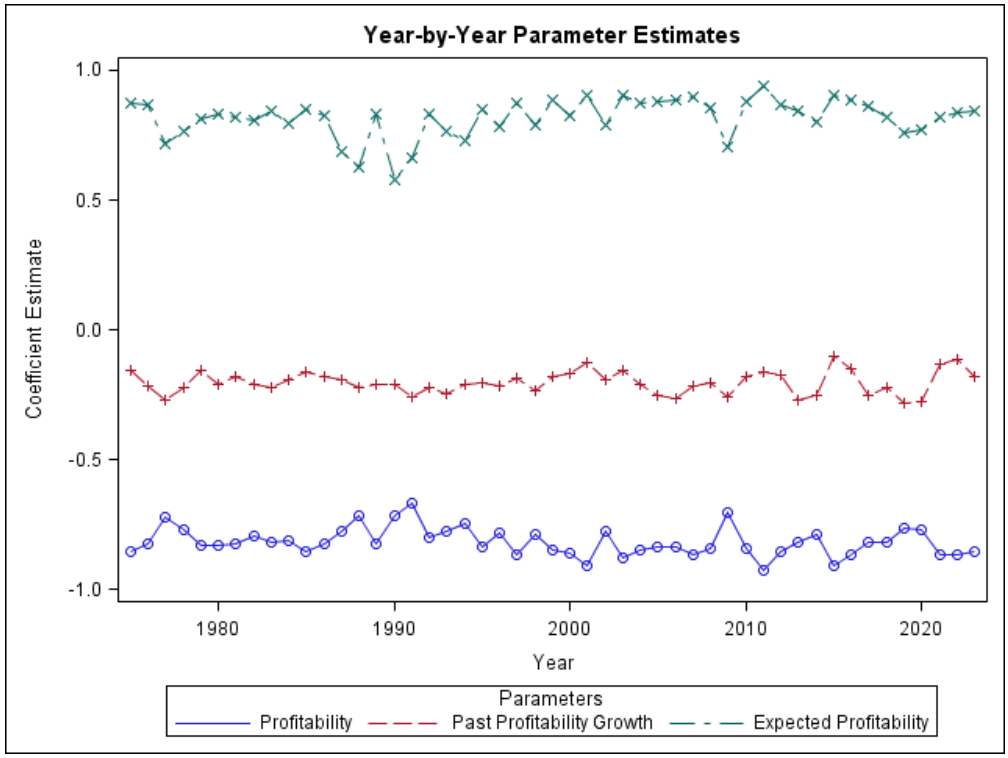
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Figure 1: Time Series of Parameter Estimates

This figure shows the year-by-year coefficients for the mean reversion regressions in Table 2. The top panel displays estimates using CBOP, while the bottom panel shows estimates using CP.



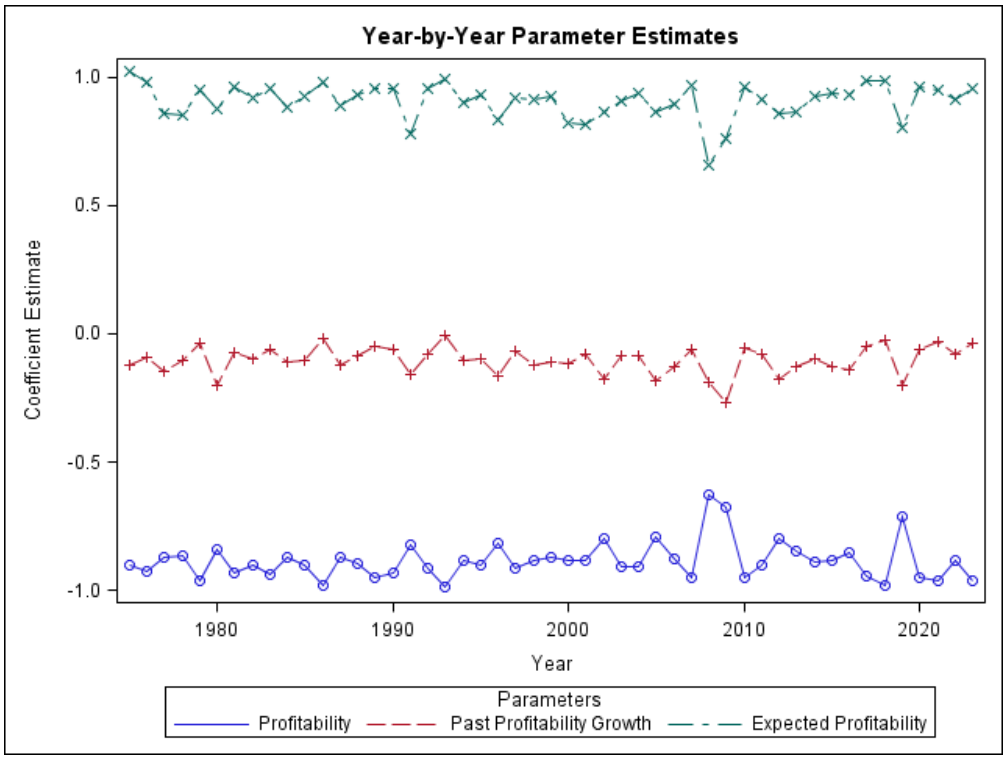
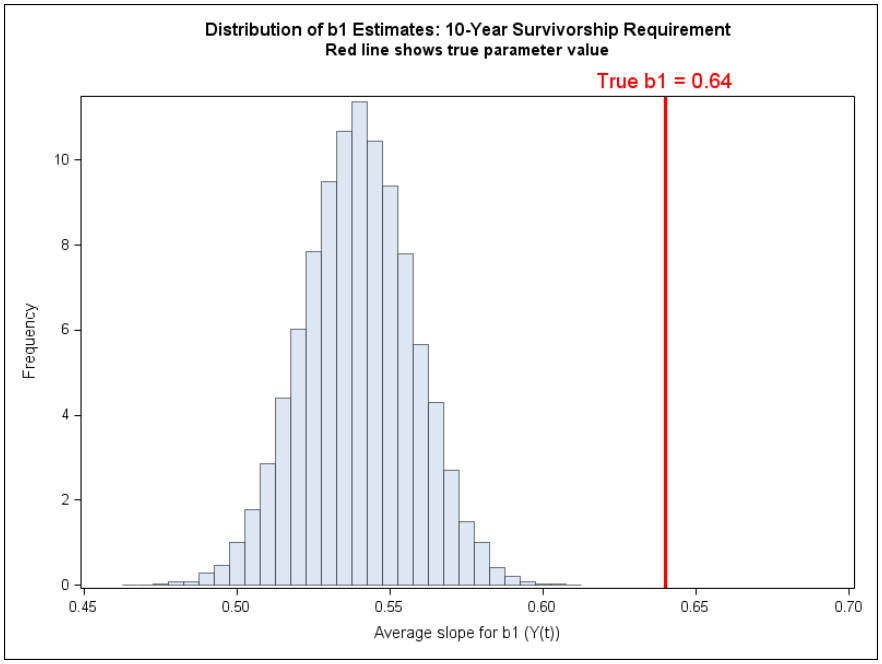


Figure 2: Distribution of Average Slopes With Survivorship Bias

This figure shows the distribution of average slopes from Fama and MacBeth (1973) regressions of $Y_{t+1} = \beta_1 Y_t + \beta_2 \Delta Y_t + \epsilon_t$ in simulated data. The data-generating process for the simulation is $Y_{t+1} = 0.64 \times Y_t - 0.20 \times \Delta Y_t + \epsilon_t$, corresponding to the baseline regression estimates in Panel A of Table 1. The error term is mean-zero standard normal with a variance of 0.0087, corresponding to the variance of residuals from the baseline regression in Table 1. Y_t is drawn from a normal distribution with a mean of 0.10 and variance of 0.125, equal to the moments from the cross-sectional distribution of profitability in the actual data. Each simulation round generates a panel of 3,000 stocks over the 1975-2024 sample period with an entry and exit rate of 3%. I calculate actual average attrition rates for deciles based on average profitability over the prior three years from the actual data. I then use these breakpoints and attrition rates to generate attrition in the simulated sample matching the actual data. For each of the 500 simulation iterations, I estimate the above regressions while requiring that a firm survive over the past 10 years. The figures show the distribution of β_1 and β_2, along with the true values from the data generating process.



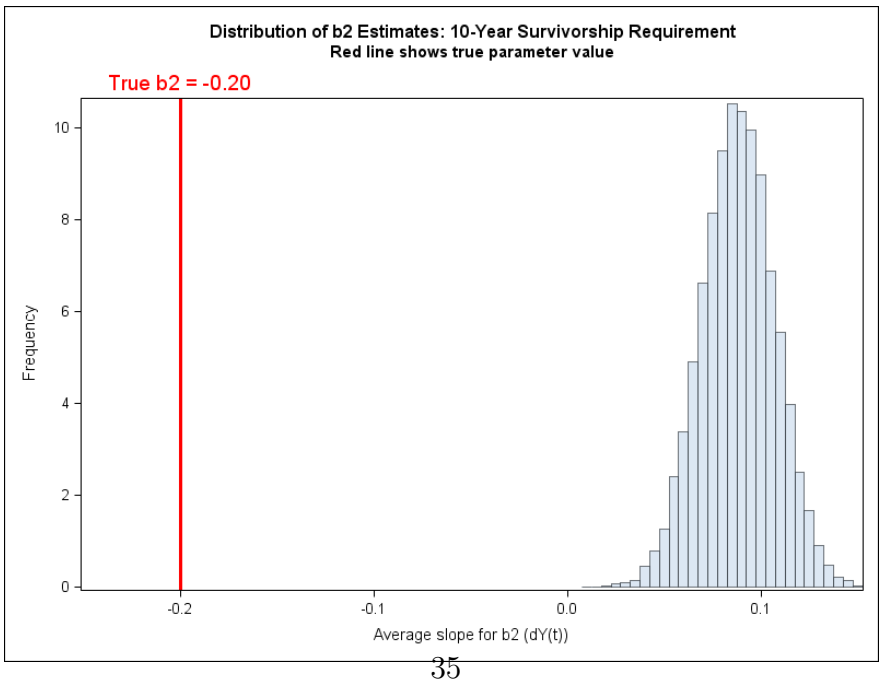


Table 1: Regressions of Future Profitability

The table contains average slopes of annual cross-sectional regressions of one ($\tau = 1$), two ($\tau = 2$), and three ($\tau = 3$) year ahead profitability on lagged variables. The regressions use two measures of profitability (Y): (a) cash based operating profitability (CBOP), computed using the balance sheet method of Ball, Gerakos, Linnainmaa, and Nikolaev (2016), and (b) cash profitability (CP), computed as in Fama and French (2018). CBOP is scaled by lagged total assets. CP removes interest expense and is scaled by lagged book equity. dA_{t-1}/A_{t-2} is percentage change in total assets from fiscal year $t-2$ to $t-1$ and dB_{t-1}/B_{t-2} is percentage change in book equity from fiscal year $t-2$ to $t-1$. Change in profitability (ΔY_t) is the level difference in scaled profitability in adjacent years. Explanatory variables are winsorized at the 1% level. The sample consists of all firms with calculable variables over the 1975-2024 period, excluding utilities, financials, and microcap firms. Microcap firms are defined as those with market value of equity below the 20th percentile from NYSE securities. Newey-West t-statistics appear in parentheses. Average N and average adj-R^2 are time series averages from the annual regressions.

	One year ahead ($\tau = 1$)			Two year ahead ($\tau = 2$)			Three year ahead ($\tau = 3$)		
Panel A: Predicting $Y_{t+\tau}$ using CBOP									
Y_t	0.559	0.404	0.637	0.461	0.302	0.541	0.413	0.249	0.494
	(27.28)	(24.42)	(37.35)	(24.43)	(19.10)	(31.55)	(22.96)	(17.66)	(29.17)
Y_{t-1}	–	0.160	–	–	0.147	–	–	0.154	–
		(20.21)			(18.16)			(13.85)	
Y_{t-2}	–	0.115	–	–	0.142	–	–	0.138	–
		(14.24)			(10.67)			(9.38)	
ΔY_t	–	–	-0.201	–	–	-0.198	–	–	-0.202
			(29.04)			(23.06)			(22.51)
Ln(B/M)	-0.028	-0.025	-0.025	-0.028	-0.024	-0.025	-0.025	-0.021	-0.022
	(10.48)	(11.48)	(11.58)	(12.05)	(12.21)	(12.59)	(10.04)	(9.97)	(9.94)
Ln(ME)	0.005	0.003	0.004	0.006	0.004	0.005	0.007	0.005	0.006
	(5.77)	(3.79)	(4.57)	(7.56)	(5.46)	(6.48)	(8.33)	(6.13)	(7.14)
dA_{t-1}/A_{t-2}	-0.013	-0.020	-0.019	-0.018	-0.025	-0.024	-0.016	-0.025	-0.022
	(6.17)	(10.06)	(8.82)	(6.80)	(6.94)	(7.17)	(5.13)	(6.39)	(5.48)
Avg. Adj-R^2	0.44	0.49	0.48	0.34	0.40	0.38	0.29	0.34	0.32
Avg. N	1,125	1,125	1,125	1,068	1,068	1,068	1,014	1,014	1,014
Panel B: Predicting $Y_{t+\tau}$ using CP									
Y_t	0.276	0.225	0.362	0.194	0.153	0.272	0.169	0.121	0.249
	(11.82)	(11.06)	(13.61)	(11.52)	(9.71)	(16.45)	(15.62)	(12.71)	(16.15)
Y_{t-1}	–	0.122	–	–	0.103	–	–	0.103	–
		(11.11)			(10.75)			(9.67)	
Y_{t-2}	–	0.097	–	–	0.087	–	–	0.090	–
		(10.05)			(11.45)			(9.23)	
ΔY_t	–	–	-0.107	–	–	-0.091	–	–	-0.094
			(8.67)			(7.81)			(11.84)
Ln(B/M)	-0.123	-0.121	-0.119	-0.077	-0.075	-0.074	-0.052	-0.050	-0.049
	(6.53)	(6.74)	(6.66)	(7.27)	(7.21)	(7.42)	(5.67)	(5.22)	(5.54)
Ln(ME)	0.030	0.021	0.026	0.033	0.026	0.030	0.036	0.029	0.033
	(5.78)	(5.15)	(5.40)	(6.62)	(6.06)	(6.19)	(6.04)	(5.62)	(5.71)
dB_{t-1}/B_{t-2}	-0.060	-0.092	-0.095	-0.043	-0.071	-0.070	-0.047	-0.076	-0.075
	(5.38)	(5.88)	(6.07)	(3.84)	(4.50)	(4.55)	(4.60)	(5.26)	(5.90)
Avg. Adj-R^2	0.18	0.22	0.21	0.09	0.12	0.11	0.07	0.10	0.09
Avg. N	1,125	1,125	1,125	1,068	1,068	1,068	1,014	1,014	1,014

Table 2: Partial Adjustment Models: Regressions of Changes in Profitability

The table contains average slopes of annual cross-sectional regressions of changes in profitability (ΔY_{t+1}) on lagged variables. The regressions use two measures of profitability: (a) cash based operating profitability (CBOP), computed using the balance sheet method of Ball et al. (2016), and (b) cash profitability (CP), computed as in Fama and French (2018). CBOP includes interest expense and is scaled by lagged total assets. CP removes interest expense and is scaled by lagged book equity. The independent variables in the regressions use profitability measures matching the dependent variable. The first column contains regressions of changes in profitability on lagged changes in profitability. The second column adds the lagged level of profitability to the first model. The third column shows an unrestricted partial adjustment model in which $\hat{Y}_t$ is derived from fitted values of first-stage regressions. First stage regressions predict Y_t using lagged asset or book equity growth, lagged profitability, the logarithm of book to market ratios, and the logarithm of market equity (as in the first column in Table 1). Variables are winsorized at the 1% level. The sample consists of all firms with calculable variables over the 1975-2024 period, excluding utilities, financials, and microcap firms. Microcap firms are defined as those with market value of equity below the 20th percentile from NYSE securities. Newey-West t-statistics appear in parentheses. Average N and average adj-R^2 are time series averages from the annual regressions.

	ΔY_{t+1} (using CBOP)			ΔY_{t+1} (using CP)		
ΔY_t	-0.346	-0.212	-0.194	-0.350	-0.100	-0.097
	(29.07)	(20.59)	(28.19)	(21.04)	(7.63)	(9.02)
Y_t	–	-0.302	-0.877	–	-0.641	-0.914
		(23.78)	(60.68)		(26.95)	(84.21)
$\hat{Y}_t$	–	–	0.908	–	–	0.983
			(43.79)			(87.67)
Avg. Adj-R^2	0.14	0.25	0.29	0.18	0.38	0.44
Avg. N	1,160	1,175	1,125	1,166	1,166	1,130

Table 3: Profitability, Past profitability, and Past Profitability Growth in Fama-MacBeth Regressions

The table reports average Fama and MacBeth (1973) regression slopes of monthly returns on lagged variables. The regressions use two measures of profitability (Y_t): (a) cash based operating profitability (CBOP), computed using the balance sheet method of Ball, Gerakos, Linnainmaa, and Nikolaev (2016), and (b) cash profitability (CP), computed as in Fama and French (2018). CBOP includes interest expense and is scaled by lagged total assets. CP removes interest expense and is scaled by lagged book equity. All regressions include prior month returns ($R_{1,1}$) and prior 11-month returns ($R_{2,12}$), the logarithm of book to market ratios and the logarithm of market equity. Regression that use CBOP and CP include dA_{t-1}/A_{t-2} or dB_{t-1}/B_{t-2} respectively as a regressor. The sample includes firms with valid data for independent variables including two lags of profitability. Panel A contains all stocks, excluding financials and utilities. Panel B excludes microcap firms (defined as those with market value of equity below the 20th percentile from NYSE securities each June). The sample period is July 1975 to December 2024. All slopes are multiplied by 100. Accounting variables are winsorized at the 1% level, as in Table 1. Newey-West t-statistics appear in parentheses. Average N and average adj-R^2 are time series averages from the monthly regressions.

	Y = CBOP			Y = CP		
Panel A: All stocks						
Y_t	1.86	1.48	2.06	0.29	0.25	0.37
	(9.27)	(8.33)	(8.38)	(5.55)	(5.51)	(5.35)
Y_{t-1}	–	0.64	–	–	0.15	–
		(3.69)			(3.16)	
ΔY_t	–	–	-0.51	–	–	-0.10
			(3.01)			(2.81)
Ln(B/M)	0.28	0.27	0.27	0.27	0.26	0.26
	(3.76)	(3.64)	(3.65)	(3.69)	(3.69)	(3.67)
Ln(ME)	-0.12	-0.13	-0.13	-0.09	-0.10	-0.09
	(3.05)	(3.35)	(3.30)	(2.15)	(2.43)	(2.35)
dA_{t-1}/A_{t-2} or dB_{t-1}/B_{t-2}	-0.35	-0.35	-0.35	-0.14	-0.15	-0.15
	(5.17)	(5.21)	(5.21)	(3.42)	(3.43)	(3.46)
$R_{1,1}$	-4.62	-4.64	-4.63	-4.55	-4.58	-4.57
	(11.78)	(11.84)	(11.82)	(11.55)	(11.64)	(11.60)
$R_{2,12}$	0.21	0.22	0.22	0.23	0.23	0.23
	(1.42)	(1.43)	(1.43)	(1.54)	(1.51)	(1.51)
Avg. Adj-R^2	0.03	0.03	0.03	0.03	0.03	0.03
Avg. N	2,541	2,541	2,541	2,541	2,541	2,541
Panel B: All but microcap stocks						
Y_t	1.33	1.03	1.56	0.26	0.23	0.35
	(6.00)	(4.72)	(6.01)	(4.38)	(4.20)	(4.45)
Y_{t-1}	–	0.52	–	–	0.11	–
		(2.36)			(2.11)	
ΔY_t	–	–	-0.53	–	–	-0.10
			(2.49)			(2.31)
Ln(B/M)	0.22	0.22	0.22	0.16	0.16	0.16
	(3.02)	(3.03)	(2.84)	(2.16)	(2.13)	(2.15)
Ln(ME)	-0.07	-0.07	-0.07	-0.06	-0.06	-0.06
	(1.79)	(1.91)	(1.91)	(1.58)	(1.70)	(1.70)
dA_{t-1}/A_{t-2} or dB_{t-1}/B_{t-2}	-0.15	-0.16	-0.17	-0.07	-0.09	-0.10
	(1.65)	(1.74)	(1.81)	(1.21)	(1.41)	(1.52)
$R_{1,1}$	-2.79	-2.81	-2.81	-2.75	-2.76	-2.76
	(6.11)	(6.16)	(6.18)	(6.00)	(6.03)	(6.02)
$R_{2,12}$	0.25	0.26	0.26	0.24	0.24	0.24
	(1.22)	(1.25)	(1.24)	(1.16)	(1.15)	(1.14)
Avg. Adj-R^2	0.05	0.05	0.05	0.05	0.05	0.05
Avg. N	1,138	1,138	1,138	1,138	1,138	1,138

Table 4: Interaction Effects in Fama-MacBeth Regressions

The table reports average Fama and MacBeth (1973) regression slopes of monthly returns on lagged variables. The specifications are similar to those in Table 3 but also include two types of interaction terms. The first interaction is between profitability and past profitability growth ($Y_t \times \Delta Y_t$). The second type of interaction is between past profitability growth and indicator variables for high or low profitability firms (HighProf and LowProf). The indicator variables are equal to one for firms in the highest (or lowest) quintile of profitability in that year using NYSE breakpoints. All regressions include the following control (Z_t) variables which are not displayed: prior month returns ($R_{1,1}$), prior 11-month returns ($R_{2,12}$), the logarithm of book to market ratios, the logarithm of market equity and investment (dA_{t-1}/A_{t-2} or dB_{t-1}/B_{t-2}). The sample includes firms with valid data for independent variables. Panel A contains all stocks, excluding financials and utilities. Panel B excludes microcap firms (defined as those with market value of equity below the 20th percentile from NYSE securities each June). The sample period is July 1975 to December 2024. All slopes are multiplied by 100. Accounting variables are winsorized at the 1% level. Newey-West t-statistics appear in parentheses. Average N and average adj-R^2 are time series averages from the monthly regressions.

	Y = CBOP		Y = CP	
Panel A: All stocks				
Y_t	2.00	2.04	0.37	0.24
	(8.17)	(7.79)	(5.23)	(4.32)
ΔY_t	-0.40	-0.36	-0.08	-0.06
	(2.29)	(1.35)	(2.35)	(0.80)
High Prof Indicator	–	-0.03	–	0.01
		(0.46)		(0.24)
Low Prof Indicator	–	-0.04	–	-0.21
		(0.49)		(2.38)
$Y_t \times \Delta Y_t$	-1.63	–	-0.04	–
	(4.22)		(2.32)	
$\Delta Y_t \times$ High Prof	–	-0.93	–	-0.15
		(3.13)		(2.10)
$\Delta Y_t \times$ Low Prof	–	0.21	–	0.06
		(0.60)		(0.76)
Avg. Adj-R^2	0.03	0.03	0.03	0.03
Avg. N	2,541	2,541	2,541	2,541
Panel B: All-but-microcap stocks				
Y_t	1.50	1.46	0.34	0.18
	(5.88)	(5.15)	(4.17)	(2.47)
ΔY_t	-0.17	-0.48	-0.08	-0.12
	(0.68)	(1.61)	(1.65)	(1.31)
High Prof Indicator	–	0.02	–	0.07
		(0.38)		(1.32)
Low Prof Indicator	–	-0.03	–	-0.21
		(0.28)		(2.41)
$Y_t \times \Delta Y_t$	-1.80	–	-0.05	–
	(2.68)		(1.85)	
$\Delta Y_t \times$ High Prof	–	-0.63	–	-0.05
		(1.98)		(0.48)
$\Delta Y_t \times$ Low Prof	–	0.52	–	0.12
		(1.22)		(1.01)
Avg. Adj-R^2	0.05	0.05	0.05	0.05
Avg. N	1,138	1,138	1,138	1,138

Table 5: Portfolio Returns of Conditional Double Sorts

Each June, all stocks (excluding financials and utilities) are independently ranked based on size, book-to-market ratios, investment, and profitability. The ranking for size and investment are descending, to reflect their correspondence with future returns. Stocks are assigned into composite quintiles based on these rankings. Within each composite rank quintile, stocks are then sorted into past profitability quintiles. The table presents value-weighted excess returns, intercepts from five-factor model time series regressions, and their t-statistics. Panel A uses CBOP as the profitability measure and dA_{t-1}/A_{t-2} as the investment metric. Panel B uses CP as the profitability measure and dB_{t-1}/B_{t-2} as the investment metric. The sample includes all stocks, excluding financials and utilities. The sample period is July 1975 to December 2024.

	Conditional ΔY_t quintiles						
Composite Rank Quintiles	Low	2	3	4	High	H-L	t-stat
CBOP							
Panel A: Excess Returns							
Low	0.65	0.52	0.65	0.66	0.97	0.32	2.00
2	0.76	0.66	0.75	0.79	0.80	0.05	0.29
3	0.87	0.80	0.92	0.97	0.80	-0.06	0.34
4	1.16	1.16	1.09	0.94	1.02	-0.15	0.85
High	1.46	1.34	1.22	1.40	0.85	-0.60	3.42
H-L	0.81	0.82	0.57	0.74	-0.11	–	–
t-stat	(3.41)	(3.34)	(2.74)	(3.43)	(0.48)	–	–
Panel B: Five-Factor Intercepts							
Low	0.13	-0.13	-0.01	-0.09	0.50	0.37	2.25
2	-0.06	-0.11	-0.05	0.01	0.01	0.07	0.42
3	-0.03	-0.16	0.17	-0.01	-0.01	0.02	0.13
4	0.20	0.07	0.05	-0.07	0.12	-0.08	-0.44
High	0.54	0.21	0.16	0.38	-0.14	-0.68	3.70
H-L	0.41	0.37	0.17	0.48	-0.64	–	–
Panel C: T-statistics							
Low	1.12	-0.32	0.03	-1.32	3.95	–	–
2	-0.51	-1.15	-0.75	0.04	0.00	–	–
3	-0.25	-1.57	1.91	-0.07	-0.08	–	–
4	1.50	0.64	0.54	-0.75	0.93	–	–
High	3.75	1.40	1.41	3.21	-0.91	–	–
H-L	2.33	1.97	1.39	3.51	3.48	–	–
CP							
Panel D: Excess Returns							
Low	0.70	0.54	0.60	0.71	0.87	0.16	1.00
2	0.66	0.68	0.78	0.77	0.77	0.10	0.53
3	0.78	0.89	0.97	0.97	0.91	0.13	0.64
4	1.05	1.29	1.03	0.91	0.95	-0.11	-0.57
High	1.29	1.50	1.38	1.20	0.85	-0.45	1.89
H-L	0.59	0.95	0.78	0.49	-0.01	–	–
t-stat	(2.34)	(3.17)	(3.36)	(2.03)	(0.06)	–	–
Panel E: Five-Factor Intercepts							
Low	0.02	-0.03	-0.04	0.11	0.27	0.24	1.49
2	-0.22	-0.20	-0.01	-0.02	-0.07	0.15	0.79
3	-0.35	-0.17	0.09	-0.01	0.01	0.37	1.91
4	-0.03	0.20	-0.02	-0.11	-0.07	-0.04	-0.19
High	0.33	0.34	0.23	-0.03	-0.31	-0.64	-2.42
H-L	0.30	0.38	0.28	-0.15	-0.58	–	–
Panel F: T-statistics							
Low	0.23	-0.37	-0.67	1.61	2.62	–	–
2	-1.49	-2.21	-0.22	-0.23	-0.74	–	–
3	-2.23	-1.46	1.07	-0.14	0.18	–	–
4	-0.22	1.81	-0.21	-0.95	-0.55	–	–
High	1.77	1.57	1.65	-0.28	-1.48	–	–
H-L	1.46	1.62	1.82	1.00	2.58	–	–

Table 6: Fama-MacBeth Regressions using Expected Profitability Derived from Analysts Forecasts

The table reports average Fama and MacBeth (1973) slopes of monthly returns on lagged variables and expected profitability ($\hat{Y}^I_{t+1|t}$) derived from IBES analysts forecasts. Lagged variables are as defined in earlier tables. $\hat{Y}^I_{t+1|t}$ is computed as follows. I first compute annualized expected earning growth rates using the ratio of the average and median one-year-ahead EPS forecast scaled by current (actual) EPS from the IBES Unadjusted US Summary Statistics file. Growth rates are only calculable if current EPS is positive. There is a minimum of six months between the EPS forecast date (`statsper`) and the end of the fiscal period for which the forecast applies (`fpedats`). I require that at least three analysts provide EPS forecasts and keep only the most recent forecast prior to June of each year. I multiply the mean or median growth rate by Y_{t-1} to obtain $\hat{Y}^I_{t+1|t}$. Columns (1) and (4), reproduce the baseline regression in Table 3 in this smaller sample. The regressions in columns (2) and (5), use average EPS forecasts to calculate growth rates. The regressions in columns (3) and (6), use a growth rate derived from median EPS forecasts. The sample period is July 1977 to December 2024. Newey-West t-statistics appear in parentheses. Average N and average adj-R^2 are time series averages from the monthly regressions.

	Y = CBOP			Y = CP		
	(1)	(2)	(3)	(4)	(5)	(6)
Y_t	0.90	–	–	0.13	–	–
	(3.59)			(1.91)		
$\hat{Y}^I_{t+1\|t}$	–	0.06	0.06	–	-0.03	-0.04
		(0.63)	(0.70)		(1.14)	(1.37)
Ln(B/M)	0.11	0.03	0.03	0.06	0.04	0.04
	(1.46)	(0.43)	(0.44)	(0.76)	(0.54)	(0.52)
Ln(ME)	-0.08	-0.08	-0.08	-0.07	-0.07	-0.07
	(1.99)	(1.96)	(1.92)	(1.91)	(1.79)	(1.80)
$R_{1,1}$	-3.28	-3.27	-3.27	-3.26	-3.24	-3.24
	(7.39)	(7.37)	(7.37)	(7.34)	(7.34)	(7.33)
$R_{2,12}$	0.46	0.46	0.46	0.47	0.47	0.47
	(2.03)	(2.04)	(2.04)	(2.10)	(2.08)	(2.09)
dA_{t-1}/A_{t-2} or dB_{t-1}/B_{t-2}	-0.29	-0.29	-0.29	-0.08	-0.08	-0.08
	(3.07)	(3.07)	(3.08)	(1.23)	(1.19)	(1.19)
Avg. Adj-R^2	0.05	0.05	0.05	0.05	0.05	0.05
Avg. N	986	986	986	986	986	986

Table 7: Fama-MacBeth Regressions using Expected Profitability Derived from Past Profitability and Past Profitability Growth

The table reports average Fama and MacBeth (1973) regression slopes of monthly returns on lagged variables, current profitability (Y_t), and expected profitability ($\hat{Y}_{t+1|t}$). $\hat{Y}_{t+1|t}$ is dervied from fitted values of first stage regressions as in the first column of Table 1. All regressions include prior month returns ($R_{1,1}$) and prior 11-month returns ($R_{2,12}$), the logarithm of book to market ratios and the logarithm of market equity. Regression that use CBOP and CP also use dA_{t-1}/A_{t-2} and dB_{t-1}/B_{t-2} respectively as regressors. In columns (1), (3), (4), and (6), the average inter-quartile return difference is computed as the time series average of each month's estimated profitability coefficient (Y_t or $\hat{Y}_{t+1|t}$) multiplied by the interquartile range of profitability. The sample for Panel A includes all stocks, excluding financials and utilities. Panel B excludes microcap firms (defined as those with market value of equity below the 20th percentile from NYSE securities each June). The sample period is July 1975 to December 2024. All slopes are multiplied by 100. Accounting variables are winsorized at the 1% level, as in Table 1. Newey-West t-statistics appear in parentheses. Average N and average adj-R^2 are time series averages from the monthly regressions.

	Y = CBOP			Y = CP		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All stocks						
Y_t	1.80	1.19	–	0.34	0.29	–
	(8.14)	(5.89)		(5.04)	(4.96)	
$\hat{Y}_{t+1\|t}$	–	1.64	2.81	–	0.50	0.77
		(4.61)	(7.15)		(2.99)	(3.98)
Ln(B/M)	0.19	0.18	0.17	0.15	0.12	0.12
	(2.40)	(2.28)	(2.23)	(2.11)	(1.89)	(1.88)
Ln(ME)	-0.10	-0.14	-0.14	-0.08	-0.12	-0.12
	(2.59)	(3.78)	(3.77)	(2.04)	(3.63)	(3.60)
$R_{1,1}$	-4.21	-4.24	-4.21	-4.19	-4.21	-4.18
	(10.50)	(10.56)	(10.47)	(10.38)	(10.47)	(10.34)
$R_{2,12}$	0.25	0.24	0.26	0.28	0.27	0.29
	(1.51)	(1.45)	(1.57)	(1.66)	(1.62)	(1.73)
dA_{t-1}/A_{t-2} or dB_{t-1}/B_{t-2}	-0.14	-0.13	-0.14	-0.05	-0.06	-0.06
	(1.96)	(1.77)	(1.85)	(1.20)	(1.24)	(1.42)
Avg. Adj-R^2	0.03	0.03	0.03	0.03	0.03	0.03
Avg. N	2,550	2,550	2,550	2,550	2,550	2,550
Avg implied IQR Return difference	0.29	–	0.35	0.11	–	0.21
			(2.06)			(2.17)
Panel B: All but microcap stocks						
Y_t	1.22	0.68	–	0.22	0.16	–
	(5.04)	(2.64)		(2.54)	(2.01)	
$\hat{Y}_{t+1\|t}$	–	1.43	2.09	–	0.56	0.69
		(5.14)	(3.26)		(3.06)	(3.36)
Ln(B/M)	0.16	0.21	0.21	0.09	0.14	0.13
	(2.09)	(2.81)	(2.78)	(1.09)	(1.55)	(1.48)
Ln(ME)	-0.07	-0.08	-0.08	-0.06	-0.09	-0.09
	(1.82)	(2.17)	(2.15)	(1.58)	(2.36)	(2.32)
$R_{1,1}$	-2.64	-2.66	-2.64	-2.65	-2.65	-2.61
	(5.80)	(5.89)	(5.81)	(5.82)	(5.84)	(5.72)
$R_{2,12}$	0.44	0.44	0.46	0.46	0.44	0.46
	(1.73)	(1.70)	(1.78)	(1.77)	(1.73)	(1.80)
dA_{t-1}/A_{t-2} or dB_{t-1}/B_{t-2}	-0.09	-0.07	-0.07	0.01	-0.00	-0.01
	(1.02)	(0.79)	(0.77)	(0.17)	(0.08)	(0.22)
Avg. Adj-R^2	0.05	0.05	0.05	0.05	0.05	0.05
Avg. N	1,132	1,132	1,132	1,132	1,132	1,132
Avg implied IQR return difference	0.17	–	0.22	0.05	–	0.12
			(1.80)			(2.19)

Table 8: Expected Profitability in Value-Weighted Fama-MacBeth Regressions

The table reports average Fama and MacBeth (1973) slopes of value-weighted regressions of monthly returns on lagged variables, current profitability (Y_t), and expected profitability ($\hat{Y}_{t+1|t}$). $\hat{Y}_{t+1|t}$ is dervied from fitted values of first stage regressions as in the first column of Table 1. All Fama-MacBeth regressions include prior month returns ($R_{1,1}$) and prior 11-month returns ($R_{2,12}$), the logarithm of book to market ratios and the logarithm of market equity. Regression that use CBOP and CP to measure profitability include also include dA_{t-1}/A_{t-2} and dB_{t-1}/B_{t-2} respectively as a regressor. The sample for Panel A includes all stocks, excluding financials and utilities. Panel B excludes microcap firms (defined as those with market value of equity below the 20th percentile from NYSE securities each June). The sample period is July 1975 to December 2024. All slopes are multiplied by 100. Accounting variables are winsorized at the 1% level, as in Table 1. Newey-West t-statistics appear in parentheses. Average N and average adj-R^2 are time series averages from the monthly regressions.

	Y = CBOP			Y = CP		
	(1)	(2)	(3)	(4)	(5)	(6)
Y_t	1.08	0.61	–	0.21	0.12	–
	(3.30)	(1.35)		(2.47)	(0.53)	
$\hat{Y}_{t+1\|t}$	–	0.89	1.68	–	0.20	0.40
		(1.85)	(2.87)		(2.43)	(2.02)
Ln(B/M)	0.14	0.13	0.12	0.03	-0.01	0.02
	(1.93)	(1.67)	(1.56)	(0.37)	(0.08)	(0.31)
Ln(ME)	-0.04	-0.07	-0.07	-0.04	-0.05	-0.04
	(1.09)	(1.69)	(1.78)	(0.91)	(1.28)	(1.00)
$R_{1,1}$	-2.04	-2.08	-2.02	-2.05	-2.06	-2.02
	(4.01)	(4.14)	(4.01)	(3.98)	(4.06)	(3.95)
$R_{2,12}$	0.52	0.51	0.52	0.53	0.53	0.55
	(2.49)	(2.45)	(2.50)	(2.53)	(2.53)	(2.61)
dA_{t-1}/A_{t-2} or dB_{t-1}/B_{t-2}	0.14	0.12	0.10	-0.05	-0.04	-0.08
	(0.96)	(0.88)	(0.70)	(0.58)	(0.48)	(0.94)
Avg. Adj-R^2	0.10	0.10	0.10	0.10	0.10	0.10
Avg. N	2,548	2,548	2,548	2,548	2,548	2,548

Table 9: Regressions of Future Profitability, 1940-1974

The table contains average slopes of annual cross-sectional regressions of one (τ=1), two (τ=2), and three (τ=3) year ahead profitability on lagged variables. The regressions use two measures of operating profitability (Y_t) without adjustments for accruals: (a) sales minus cost of goods sold minus SG&A (less R&D), scaled by lagged assets, and (b) sales less the sum of cost of goods sold, SG&A, and interest expense, scaled by lagged book equity. dA_{t-1}/A_{t-2} is percentage change in total assets from fiscal year $t-2$ to $t-1$ and dB_{t-1}/B_{t-2} is percentage change in book equity from fiscal year $t-2$ to $t-1$. Change in operating profitability (ΔY_t) is the level difference in scaled operating profitability in adjacent years. All coefficients are reported as is except dA_{t-1}/A_{t-2}, dB_{t-1}/B_{t-2}, and Ln(ME) which are multiplied by 10. Explanatory variables are winsorized at the 1% level. The sample consists of all firms with calculable variables over the 1940-1974 period. Newey-West t-statistics appear in parentheses. Average N and average adj-R^2 are time series averages from the annual regressions.

	One year ahead ($\tau = 1$)			Two year ahead ($\tau = 2$)			Three year ahead ($\tau = 3$)		
Panel A: Predicting firm-level operating profitability									
Y_t	0.705	0.613	0.730	0.566	0.406	0.611	0.492	0.323	0.547
	(31.93)	(21.20)	(34.52)	(17.61)	(14.70)	(17.57)	(12.98)	(11.97)	(13.77)
Y_{t-1}	–	0.090	–	–	0.159	–	–	0.178	–
		(3.51)			(6.77)			(9.15)	
Y_{t-2}	–	0.050	–	–	0.070	–	–	0.065	–
		(2.18)			(3.37)			(3.42)	
ΔY_t	–	–	-0.101	–	–	-0.190	–	–	-0.224
			(2.80)			(4.98)			(7.61)
Ln(B/M)	-0.025	-0.022	-0.024	-0.029	-0.026	-0.028	-0.031	-0.028	-0.029
	(9.51)	(9.70)	(9.74)	(7.51)	(7.39)	(7.59)	(6.14)	(6.07)	(6.23)
Ln(ME)	-0.003	-0.005	-0.003	-0.008	-0.008	-0.009	-0.005	-0.005	-0.005
	(0.41)	(0.58)	(0.41)	(0.66)	(0.64)	(0.70)	(0.33)	(0.34)	(0.34)
dA_{t-1}/A_{t-2}	-0.002	-0.004	-0.004	-0.003	-0.006	-0.006	-0.003	-0.007	-0.007
	(3.22)	(6.00)	(4.22)	(2.97)	(6.72)	(5.99)	(3.37)	(7.93)	(9.59)
Avg. Adj-R^2	0.64	0.66	0.66	0.48	0.51	0.50	0.41	0.44	0.43
Avg. N	987	902	987	958	876	958	933	853	933
Panel B: Predicting equity-level operating profitability									
Y_t	0.626	0.586	0.647	0.441	0.360	0.489	0.343	0.254	0.394
	(19.05)	(14.34)	(24.59)	(12.38)	(9.43)	(14.67)	(10.72)	(10.06)	(10.75)
Y_{t-1}	–	0.044	–	–	0.104	–	–	0.136	–
		(1.36)			(2.84)			(4.88)	
Y_{t-2}	–	0.043	–	–	0.043	–	–	0.023	–
		(2.89)			(2.19)			(1.16)	
ΔY_t	–	–	-0.042	–	–	-0.123	–	–	-0.137
			(1.28)			(3.12)			(3.51)
Ln(B/M)	-0.059	-0.056	-0.057	-0.068	-0.064	-0.064	-0.071	-0.067	-0.066
	(5.41)	(12.51)	(12.99)	(11.35)	(10.11)	(9.97)	(9.69)	(8.73)	(8.48)
Ln(ME)	-0.018	-0.022	-0.017	-0.031	-0.030	-0.030	-0.026	-0.030	-0.024
	(0.84)	(1.08)	(0.77)	(0.94)	(1.14)	(0.91)	(0.75)	(0.87)	(0.69)
dB_{t-1}/B_{t-2}	-0.002	-0.006	-0.004	-0.000	-0.006	-0.006	-0.003	-0.009	-0.008
	(1.44)	(2.42)	(1.92)	(0.22)	(1.95)	(1.99)	(2.24)	(4.45)	(4.20)
Avg. Adj-R^2	0.55	0.58	0.56	0.37	0.40	0.39	0.29	0.32	0.31
Avg. N	952	865	952	921	837	921	895	814	895

Table 10: Profitability, Past Profitability Growth, and Expected Profitability in Fama-MacBeth Regressions, 1940-1974

The table reports average Fama and MacBeth (1973) regression slopes of monthly returns on lagged variables. The regressions use two measures of operating profitability (Y_t) without adjustments for accruals: (a) sales minus cost of goods sold minus SG&A (less R&D), scaled by lagged assets, and (b) sales less the sum of cost of goods sold, SG&A, and interest expense, scaled by lagged book equity. Columns (1) and (2) use the level and past growth in profitability. Expected profitability ($\hat{Y}_{t+1|t}$) is based on fitted values from a first-stage cross-sectional regressions that use Y_t, ΔY_t, Ln(B/M), Ln(ME), and dA_{t-1}/A_{t-2} or dB_{t-1}/B_{t-2} as regressors. All slopes are multiplied by 100. Accounting variables are winsorized at the 1% level. The sample consists of all firms with calculable variables over the 1940-1974 period. Newey-West t-statistics appear in parentheses. Average N and average adj-R^2 are time series averages from the annual regressions.

	(1)	(2)	(3)	(4)
Panel A: Firm-level operating profitability scaled by lagged assets				
Y_t	0.81	1.11	-0.17	–
	(2.70)	(3.53)	(0.36)	
ΔY_t	–	-1.08	–	–
		(2.37)		
$\hat{Y}_{t+1\|t}$	–	–	1.16	0.93
			(2.34)	(2.20)
Ln(B/M)	0.33	0.34	0.27	0.27
	(4.14)	(4.17)	(3.07)	(2.99)
Ln(ME)	-0.11	-0.11	-0.11	-0.11
	(2.27)	(2.30)	(2.07)	(2.05)
dA_{t-1}/A_{t-2}	-0.00	-0.00	-0.00	-0.00
	(0.90)	(1.49)	(0.53)	(0.32)
$R_{1,1}$	-8.30	-8.35	-8.05	-8.09
	(14.47)	(14.64)	(14.13)	(14.26)
$R_{2,12}$	0.90	0.90	0.91	0.93
	(4.32)	(4.31)	(4.58)	(4.66)
Avg. Adj-R^2	0.07	0.07	0.07	0.07
Avg. N	935	935	935	935
Panel B: Equity-level operating profitability scaled by lagged assets				
Y_t	0.28	0.57	0.03	–
	(1.78)	(3.41)	(0.14)	
ΔY_t	–	-0.64	–	–
		(3.31)		
$\hat{Y}_{t+1\|t}$	–	–	0.70	0.74
			(2.63)	(3.21)
Ln(B/M)	0.34	0.36	0.32	0.32
	(4.14)	(4.28)	(3.47)	(3.48)
Ln(ME)	-0.11	-0.11	-0.101	-0.10
	(2.21)	(2.22)	(2.08)	(2.03)
dB_{t-1}/B_{t-2}	0.00	-0.00	-0.00	-0.00
	(0.79)	(0.39)	(0.46)	(0.32)
$R_{1,1}$	-8.04	-8.07	-8.01	-8.04
	(13.90)	(14.10)	(13.79)	(13.91)
$R_{2,12}$	0.93	0.93	0.93	0.95
	(4.42)	(4.41)	(4.58)	(4.64)
Avg. Adj-R^2	0.07	0.07	0.07	0.07
Avg. N	911	911	937	937

Table 11: Regressions of Future Profitability, International Stocks

The table contains average slopes of annual cross-sectional regressions of one ($\tau = 1$), two ($\tau = 2$), and three ($\tau = 3$) year ahead profitability on lagged variables. The regressions use two measures of profitability (Y): (a) cash based operating profitability (CBOP), computed using the balance sheet method of Ball, Gerakos, Linnainmaa, and Nikolaev (2016), and (b) cash profitability (CP), computed as in Fama and French (2018). CBOP is scaled by lagged total assets. CP removes interest expense and is scaled by lagged book equity. dA_{t-1}/A_{t-2} is percentage change in total assets from fiscal year $t-2$ to $t-1$ and dB_{t-1}/B_{t-2} is percentage change in book equity from fiscal year $t-2$ to $t-1$. Change in profitability (ΔY_t) is the level difference in scaled profitability in adjacent years. Explanatory variables are winsorized at the 1% level. The sample consists ex-US stocks with foreign incorporation codes from 41 countries listed in Appendix B. Firms below the 25th percentile in the distribution of USD market capitalization at the end of June are excluded from the sample. The sample period is 1991-2024. Newey-West t-statistics appear in parentheses. Average N and average adj-R^2 are time series averages from the annual regressions.

	One year ahead ($\tau = 1$)			Two year ahead ($\tau = 2$)			Three year ahead ($\tau = 3$)		
Panel A: Predicting $Y_{t+\tau}$ using CBOP									
Y_t	0.700	0.459	0.741	0.625	0.421	0.657	0.547	0.359	0.586
	(9.83)	(8.66)	(12.50)	(7.75)	(7.79)	(8.98)	(6.14)	(5.87)	(7.15)
Y_{t-1}	–	0.205	–	–	0.168	–	–	0.157	–
		(12.00)			(8.07)			(7.58)	
Y_{t-2}	–	0.093	–	–	0.086	–	–	0.088	–
		(5.32)			(4.15)			(4.35)	
ΔY_t	–	–	-0.258	–	–	-0.214	–	–	-0.200
			(12.03)			(8.29)			(7.45)
Ln(B/M)	-0.003	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.88)	(2.14)	(1.81)	(2.47)	(2.75)	(2.93)	(1.70)	(1.44)	(1.47)
Ln(ME)	0.004	0.002	0.003	0.003	0.002	0.002	0.003	0.002	0.002
	(1.68)	(1.57)	(1.66)	(1.33)	(1.09)	(1.18)	(1.29)	(0.77)	(1.82)
dA_{t-1}/A_{t-2}	-0.011	-0.016	-0.016	-0.009	-0.017	-0.015	-0.008	-0.017	-0.014
	(2.50)	(1.56)	(1.79)	(2.38)	(1.87)	(1.70)	(1.64)	(2.43)	(2.05)
Avg. Adj-R^2	0.61	0.66	0.65	0.54	0.57	0.52	0.47	0.51	0.50
Avg. N	10,755	10,755	10,755	10,418	10,418	10,418	9,642	9,642	9,642
Panel B: Predicting $Y_{t+\tau}$ using CP									
Y_t	0.634	0.444	0.679	0.550	0.379	0.590	0.491	0.305	0.544
	(8.63)	(7.07)	(10.93)	(7.20)	(6.96)	(8.63)	(6.59)	(5.91)	(7.54)
Y_{t-1}	–	0.163	–	–	0.141	–	–	0.154	–
		(12.30)			(7.05)			(5.47)	
Y_{t-2}	–	0.100	–	–	0.098	–	–	0.119	–
		(5.58)			(7.93)			(4.80)	
ΔY_t	–	–	-0.190	–	–	-0.168	–	–	-0.191
			(10.59)			(8.27)			(6.12)
Ln(B/M)	-0.050	-0.057	-0.053	-0.033	-0.037	-0.035	-0.024	-0.026	-0.026
	(1.95)	(2.22)	(2.13)	(1.98)	(2.04)	(2.04)	(1.92)	(1.74)	(1.80)
Ln(ME)	0.001	-0.001	-0.001	-0.001	-0.003	-0.003	0.009	-0.006	-0.007
	(0.13)	(0.20)	(0.08)	(0.11)	(0.41)	(0.32)	(0.54)	(0.40)	(0.45)
dB_{t-1}/B_{t-2}	-0.028	-0.103	-0.070	-0.022	-0.104	-0.066	-0.018	-0.108	-0.066
	(2.30)	(2.20)	(2.12)	(2.34)	(2.07)	(2.19)	(1.24)	(2.38)	(2.64)
Avg. Adj-R^2	0.51	0.56	0.55	0.43	0.47	0.35	0.35	0.39	0.37
Avg. N	10,563	10,563	10,563	10,187	10,187	10,187	9,406	9,406	9,406

Table 12: Profitability, Past Profitability Growth, and Expected Profitability in Fama-MacBeth Regressions, International Stocks

The table reports average Fama and MacBeth (1973) regression slopes of monthly returns on lagged variables. The regressions use two measures of profitability (Y_t): (a) cash based operating profitability (CBOP), computed using the balance sheet method of Ball, Gerakos, Linnainmaa, and Nikolaev (2016), and (b) cash profitability (CP), computed as in Fama and French (2018). dA_{t-1}/A_{t-2} is percentage change in total assets from fiscal year $t-2$ to $t-1$ and dB_{t-1}/B_{t-2} is percentage change in book equity from fiscal year $t-2$ to $t-1$. Change in profitability (ΔY_t) is the level difference in scaled profitability in adjacent years. Explanatory variables are winsorized at the 1% level. Columns (1) and (2) use the level and past growth in profitability. Expected profitability ($\hat{Y}_{t+1|t}$) is based on fitted values from a first-stage cross-sectional regressions that use Y_t, ΔY_t, Ln(B/M), Ln(ME), and dA_{t-1}/A_{t-2} or dB_{t-1}/B_{t-2} as regressors. All slopes are multiplied by 100. Accounting variables are winsorized at the 1% level. The sample consists ex-US stocks with foreign incorporation codes from 41 countries listed in Appendix **??**. Firms below the 25th percentile in the distribution of USD market capitalization at the end of June are excluded from the sample. The sample period is July 1991 and December 2024. Newey-West t-statistics appear in parentheses. Average N and average adj-R^2 are time series averages from the cross-sectional regressions.

	(1)	(2)	(3)	(4)
Panel A: CBOP				
Y_t	0.75	0.96	0.06	–
	(2.26)	(2.58)	(0.19)	
ΔY_t	–	-0.44	–	–
		(1.84)		
$\hat{Y}_{t+1\|t}$	–	–	1.28	1.32
			(2.46)	(2.92)
Ln(B/M)	0.38	0.39	0.38	0.38
	(4.24)	(4.38)	(4.67)	(4.67)
Ln(ME)	-0.02	-0.02	-0.05	-0.05
	(0.53)	(0.59)	(1.28)	(1.23)
dA_{t-1}/A_{t-2}	-0.26	-0.23	-0.17	-0.15
	(1.63)	(1.46)	(1.10)	(1.03)
$R_{1,1}$	-0.37	-0.41	-0.94	-0.91
	(0.58)	(0.65)	(1.34)	(1.29)
$R_{2,12}$	0.41	0.41	0.30	0.31
	(1.78)	(1.82)	(0.89)	(0.92)
Avg. Adj-R^2	0.07	0.07	0.07	0.07
Avg. N	11,273	11,273	10,868	10,868
Panel B: CP				
Y_t	0.20	0.29	-0.02	–
	(1.81)	(1.92)	(0.18)	
ΔY_t	–	-0.18	–	–
		(2.27)		
$\hat{Y}_{t+1\|t}$	–	–	0.48	0.45
			(2.40)	(2.06)
Ln(B/M)	0.37	0.37	0.36	0.36
	(3.90)	(3.90)	(4.36)	(4.6)
Ln(ME)	-0.02	-0.03	-0.06	-0.05
	(0.59)	(0.71)	(1.36)	(1.36)
dB_{t-1}/B_{t-2}	-0.05	-0.05	-0.10	-0.10
	(0.51)	(0.49)	(1.20)	(1.20)
$R_{1,1}$	-0.29	-0.34	-0.74	-0.74
	(0.44)	(0.52)	(1.03)	(1.23)
$R_{2,12}$	0.39	0.38	0.29	0.30
	(1.56)	(1.57)	(0.84)	(0.85)
Avg. Adj-R^2	0.07	0.07	0.07	0.07
Avg. N	11,156	11,156	10,719	10,719

Appendix Tables

Table A1: Portfolio Returns: Current and Expected Profitability

Quintiles are formed each June based on profitability (Y_t) or expected profitability ($\hat{Y}_{t+1|t}$). The table shows intercepts time series regressions from (i) three-factor models that use the three-factor version of SMB and HML, and (ii) four-factor models that use the five-factor versions of SMB, HML, and CMA. The sample includes all stocks, excluding financials and utilities. The sample period is July 1975 to December 2024.

	Low	2	3	4	High	H-L
Panel A: Portfolios formed using Y_t (CBOP)						
FF3	-0.39	-0.16	0.01	0.07	0.20	0.59
	(4.67)	(2.40)	(0.18)	(1.43)	(4.74)	(5.91)
FF4	-0.38	-0.19	-0.04	0.02	0.22	0.60
	(4.47)	(2.81)	(0.78)	(0.46)	(5.11)	(5.90)
Panel B: Portfolios formed using $\hat{Y}_{t+1\|t}$ (CBOP)						
FF3	-0.66	-0.34	0.04	-0.06	0.15	0.81
	(5.32)	(3.97)	(0.54)	(1.22)	(4.26)	(6.07)
FF4	-0.62	-0.32	0.02	0.08	0.14	0.76
	(4.87)	(3.73)	(0.32)	(1.56)	(3.72)	(5.53)
Panel C: Portfolios formed using Y_t (CP)						
FF3	-0.30	-0.11	0.04	0.04	0.24	0.54
	(4.14)	(1.86)	(0.69)	(1.07)	(5.29)	(5.69)
FF4	-0.30	-0.15	-0.01	0.03	0.24	0.54
	(3.99)	(2.50)	(0.10)	(0.67)	(5.38)	(5.60)
Panel D: Portfolios formed using $\hat{Y}_{t+1\|t}$ (CP)						
FF3	-0.46	-0.15	-0.17	-0.08	0.10	0.56
	(3.68)	(1.39)	(2.20)	(1.36)	(3.12)	(4.06)
FF4	-0.46	-0.14	-0.11	-0.05	0.10	0.56
	(3.46)	(1.26)	(1.47)	(0.86)	(2.27)	(3.66)

Table A2: Profitability, Past Profitability Growth, and Expected Profitability in Large-Cap International Stocks

The table reports selected average Fama and MacBeth (1973) regression slopes of monthly returns on lagged variables. Only regression slopes pertaining to profitability are shown (the regressions also include Ln(B/M), Ln(ME), dA_{t-1}/A_{t-2} or dB_{t-1}/B_{t-2}, $R_{1,1}$, and $R_{2,12}$). The regressions use two measures of profitability (Y_t): (a) cash based operating profitability (CBOP), computed using the balance sheet method of Ball, Gerakos, Linnainmaa, and Nikolaev (2016), and (b) cash profitability (CP), computed as in Fama and French (2018). CBOP includes interest expense and is scaled by lagged total assets. CP removes interest expense and is scaled by lagged book equity. Columns (1) and (2) use the level and past growth in profitability. Expected profitability ($\hat{Y}_{t+1|t}$) is based on fitted values from a first-stage cross-sectional regressions that use Y_t, ΔY_t, Ln(B/M), Ln(ME), and dA_{t-1}/A_{t-2} or dB_{t-1}/B_{t-2} as regressors. All slopes are multiplied by 100. Accounting variables are winsorized at the 1% level. The sample consists ex-US stocks with foreign incorporation codes from 41 countries listed in Appendix **??**. Firms below the 90th percentile in the distribution of USD market capitalization at the end of June are excluded from the sample. The sample period is July 1991 and December 2024. Newey-West t-statistics appear in parentheses. Average N and average adj-R2 are time series averages from the cross-sectional regressions.

The table reports average Fama and MacBeth (1973) regression slopes of monthly returns on lagged variables. The regressions use two measures of profitability (Y_t): (a) cash based operating profitability (CBOP), computed using the balance sheet method of Ball, Gerakos, Linnainmaa, and Nikolaev (2016), and (b) cash profitability (CP), computed as in Fama and French (2018). dA_{t-1}/A_{t-2} is percentage change in total assets from fiscal year $t-2$ to $t-1$ and dB_{t-1}/B_{t-2} is percentage change in book equity from fiscal year $t-2$ to $t-1$. Change in profitability (ΔY_t) is the level difference in scaled profitability in adjacent years. Explanatory variables are winsorized at the 1% level. Columns (1) and (2) use the level and past growth in profitability. Expected profitability ($\hat{Y}_{t+1|t}$) is based on fitted values from a first-stage cross-sectional regressions that use Y_t, ΔY_t, Ln(B/M), Ln(ME), and dA_{t-1}/A_{t-2} or dB_{t-1}/B_{t-2} as regressors. All slopes are multiplied by 100. Accounting variables are winsorized at the 1% level. The sample consists ex-US stocks with foreign incorporation codes from 41 countries listed in Appendix B. Firms below the 25th percentile in the distribution of USD market capitalization at the end of June are excluded from the sample. The sample period is July 1991 and December 2024. Newey-West t-statistics appear in parentheses. Average N and average adj-R2 are time series averages from the cross-sectional regressions.

	(1)	(2)	(3)	(4)
Panel A: CBOP				
Y_t	0.67	0.89	0.03	–
	(1.79)	(2.35)	(0.07)	
ΔY_t	–	-0.72	–	–
		(2.05)		
$\hat{Y}_{t+1\|t}$	–	–	2.04	2.08
			(2.64)	(3.21)
Avg. Adj-R^2	0.12	0.12	0.12	0.12
Avg. N	1,522	1,522	1,522	1,522
Panel B: CP				
Y_t	0.12	0.20	0.02	–
	(1.96)	(1.45)	(0.14)	
ΔY_t	–	-0.23	–	–
		(2.59)		
$\hat{Y}_{t+1\|t}$	–	–	0.54	0.56
			(2.58)	(2.59)
Avg. Adj-R^2	0.11	0.11	0.11	0.11
Avg. N	1,504	1,504	1,504	1,504